HELSINKI SCHOOL OF ECONOMICS (HSE)
Department of Accounting and Finance

THE EFFECT OF HIGHER MOMENTS ON MUTUAL FUND PERFORMANCE EVALUATION AND RISK MEASUREMENT

Finance
Master´s thesis
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Spring 2005

Approved by the Council of the Department 1 / 3 2005 and awarded
the grade erinomainen, 80 pistettä.
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Abstract
February 21, 2005

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PURPOSE OF THE STUDY

The objective of this thesis is to study the effect of non-normally distributed fund returns on risk-adjusted performance evaluation and risk measurement. More specifically, I try to answer the research problem, which is defined as: "Do we need alternative performance evaluation techniques other than the mean-variance framework to assess the performance and the risk levels of Finnish mutual funds of all types?"

DATA AND METHODOLOGY

This thesis utilises the daily closing net asset values of 67 mutual funds that are registered in Finland. The data are obtained from Investment Research Finland and reach from January 1st, 1999 to December 31st, 2003. The benchmark index data are gathered from DataStream Database. The sample funds are ranked according to performance measurement frameworks, which are presented in the theoretical part of this study. In addition, the sample funds are ranked according to different risk proxies. To examine the effect of higher moments on performance evaluation and risk measurement, I employ the Spearman ranking correlation test. To investigate the exploitation of asymmetrical investment strategies this study uses scatter charts.

RESULTS

The results suggest that the mean-variance framework is fairly sufficient for evaluating the risk-adjusted performance of Finnish mutual funds. However, the results also show that the higher distributional moments are complicating the performance assessment in some particular cases. Therefore, this study recommends that Omega measure should be employed when the risk and reward characteristics of risk and hedge funds are evaluated. This holds also for some funds with investment focus in global equities.

This study finds very weak evidence that Finnish fund managers would have been using negatively skewed investment strategies.

KEYWORDS

Performance evaluation, risk measurement, higher moments, non-normally distributed returns, Omega

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KORKEAMPIEN MOMENTTIEN VAIKUTUS SIJOITUSRAHASTOIDEN TULOKSELLISUUDEN ARVIOINNISSA JA RISKIN MITTAAMISESSA

TUTKIMUKSEN TAVOITTEET

Tutkimuksen tavoitteena on tarkastella epänormaalisten tuottojakaumien vaikutusta riskikorjatun tuoton arvioinnissa ja riskin mittaamisessa. Tarkemmin sanoen, yritän vastata tutkimusongelmaan, joka on määritelty seuraavasti: "Tarvitaanko keskiarvovarianssiteorian rinnalle muita vaihtoehtoisia tapoja suomalaisten rahastojen tuloksellisuuden ja riskillisyyden arvioimisessa rahastotyypistä huolimatta?"

AINEISTO JA MENETELMÄT

Tutkielma hyödyntää 67 Suomeen rekisteröidyn rahaston päivän päätösnettovarallisuusarvoja. Aineisto on saatu Sijoitustutkimuksesta ja se on ajalta 1.1.1999 – 31.12.2003. Viiteindeksit on kerätty Datastream tietokannasta. Otosrahastot on asetettu paremmuusjärjestykseen jokaisella tuotto/riskimittarilla, jotka on esitetty tutkimuksen teoriaosassa. Otosrahastot on myös rankattu eri riskimittareilla. Korkeampien momenttien vaikutuksen tutkimisessa käytän Spearmanin järjestyskorrelaatiotestiä. Epäsymmetristen sijoitusstrategioiden hyödyntämisen analysoinnissa tutkimuksessa käytetään pistekaavioita.

TULOKSET

Tulosten mukaan keskiarvovarianssiteoria on melko pätevä arvioimaan suomalaisten rahastojen riskikorjattua tuottoa. Tulokset osoittavat kuitenkin että joissain tapauksissa korkeammat momentit vaikeuttavat tuloksellisuuden arvioimista. Tämän vuoksi tutkimus ehdottaa että vipu- ja hedgerahastojen tuloksellisuuden ja riskin arvioinnissa käytettäisiin Omega-mittaria. Tämä koskee myös joitain maailmanlaajuisesti sijoittavia osakerahastoja.

Tutkimuksessa saadaan erittäin heikkoja todisteita siitä että suomalaiset rahastonhoitajat olisivat käyttäneet hyväkseen negatiivisesti vinoja sijoitusstrategioita.

AVAINSANAT

Tuloksellisuuden arviointi, riskin mittaaminen, korkeammat momentit, epänormaalisti jakautuneet tuotot, Omega

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1. INTRODUCTION

1.1 Background and motivation

The increased volatility in financial markets over the past few years has caused several unfavourable surprises for investment managers and investors. The unexpected performance of financial markets has stimulated investment managers and investors to search for alternative investment strategies: rather than outperform the relevant benchmark index, they may seek to achieve some target rate of return or to protect capital. In this framework traditional asset allocation and performance evaluation based on the mean-variance approach may no longer appropriately capture the risk and reward properties of high volatile and non-normal distributed returns. Hence, the academic research has introduced alternative methods to capture the bias of the traditional performance measures.

Practitioners assert that investors care about higher moments of the returns distribution than the first two ones, namely mean and variance (or standard deviation). Also, the underlying assumption in the mean-variance framework that all the investors follow a quadratic utility function has been heavily questioned by number of papers. Therefore, the financial literature has been developing the traditional mean-variance performance measurement framework to take into account higher moments than mean and variance.

An alternative approach to the mean-variance uses downside deviation as proxy for investment risk. This approach is called the mean-semi-variance framework and it focuses only on the returns below specific return target in risk quantification. This approach encompasses also the asymmetrical shape of a return distribution, and therefore its proponents argue that it is superior to the mean-variance framework.

Another major problem in risk quantification is the fat-tailed problem. The fat-tailed problem refers to a phenomenon that the probability of extreme losses or gains is higher in a fat-tailed distribution than in a Normal distribution. The major tool to deal with the problem is the Value-at-Risk approach, which is applied in the context of performance measurement as well.

Recently, a major step was taken in capturing the biases in empirical financial returns when Keating and Shadwick (2002a) introduced their new performance measure: the Omega statistic, which incorporates all the moments of the return distribution and requires no assumption on the utility function of a risk-averse investor. Omega is based on simple probabilities resulting directly from the information contained within the historic return data for a particular investment. The authors argue that Omega provides a full characterisation of risk and reward properties of a return distribution.

Samuelson argued as early as in the 1970 that non-normality, and skewness in particular, can be diversified away in well diversified portfolios. Yet the recent developments in the financial markets show that we should capture the biases in fund return distributions as well. This is supported by Asikainen (2002) who reports that mutual funds marketed in Finland show non-normally distributed returns. Therefore, in the tumultuous world today, we should have sufficient tools to take into account issues of non-normality.

1.2 Purpose and contribution

This thesis aims to answer the primary research question which is summarised as follows: "Do we need alternative performance evaluation techniques other than the mean-variance framework to assess the performance and the risk levels of Finnish mutual funds of all types?"

More specifically, I further divide the research problem into four components as:

1) Are Finnish mutual fund returns normally distributed?
2) Do the higher distributional moments have an effect on performance evaluation and risk measurement of Finnish mutual funds?
3) Have Finnish fund managers exploited asymmetrical investment strategies?
4) Do data frequency changes have an effect on performance evaluation and risk measurement?

Based on the answers for these four questions I try to give answer for the primary research question.

The main contribution of this study is that it uses a robust tool for evaluating the risk-adjusted performance of non-normally distributed returns. There are no studies that have employed Omega framework, which includes all the distributional moments, in examining the effect of higher moments on Finnish fund performance. For example Asikainen (2002) focuses only on the first four moments.

In addition, this thesis tries shed light on the question whether the non-normality is a more severe problem in some particular fund markets. To give answer for this question, the total sample of 67 funds registered in Finland is further divided into six sub-samples according to their asset class and geographical investment orientation.

Further, this study scrutinises the effect of higher moments on the risk-adjusted performance evaluation and the risk measurement in detail. In addition to conducting the study using different risk-adjusted performance measures, I also focus on the risk side separately and examine the impact of higher moments on the risk measurement. By doing this I try to analyse whether risk proxy selection, and therefore return non-normality affect the risk ordering of Finnish mutual funds.

This thesis also tries to find reasons for the return non-normality of Finnish mutual funds reported by Asikainen (2002). It is an interesting phenomenon, since if we consider it in light of the Samuelson (1970), Levy and Markowitz (1979) and Kroll, Levy and Markowitz (1984) finding that non-normality, skewness in particular, can be diversified away in well diversified portfolios. Yet, the financial literature has recently documented stylized facts about the prices of options. Namely, for example put options have been found to be consistently overpriced. Accordingly, this study tries to find evidence on the non-normally distributed fund returns by utilising the recent insights from this field. In particular, I try to find evidence on the question whether the Finnish fund managers have deliberately exploited asymmetrical investment strategies such as a short OTM put option – a short index strategy.

Finally, I also investigate the effect of data frequency changes on non-normality, and therefore on the risk-adjusted performance evaluation and risk measurement of Finnish mutual funds. Vaihekoski (1997) study on Finnish individual asset returns reports that the returns show decreasing non-normality when the observation level increases. To my knowledge there is no study that would have examined the effect of data frequency changes on the non-normality of fund returns.

1.3 Results

The main finding of this thesis is that in the most cases the risk-adjusted performance of Finnish mutual funds can be well evaluated by the mean-variance framework alone. However, the return distributions of risk and hedge funds are affected by the higher moments than order four, and therefore they cannot be evaluated sufficiently by the traditional mean-variance framework or its adjusted forms. The adequate performance measure that copes with the biased returns of risk and hedge funds is Omega. This holds also for some equity funds with global investment focus.

In addition, although the majority of the sample funds show persistent negative skewness, this study finds very weak or no evidence that Finnish fund managers would have systemically exploited negatively skewed or other asymmetrical investment strategies.

1.4 Limitations

This study has methodological limitations. In addition, this study makes several simplifications and assumptions that may affect the robustness of obtained results. First, this analysis focuses on historical returns and implicitly assumes that past returns can be replicated in the future. Second, this study aims to find differences between the pay-out profiles of different mutual fund sectors and examines six different fund classes. Thus, there is a trade-off between the observation period and sample size. To ensure robustness of results, there has to be sufficient number of funds in each sub-sample. For this reason the observation period of this study is short, from 1999 to 2003. The number of funds in each fund class is still rather limited which may weaken the reliability of the results. Third, the results of this study are subject to survivorship bias. However, this study compares different evaluation frameworks and does not attempt to examine the Finnish mutual fund industry as a whole, and therefore survivorship bias can be ignored. Fourth, the loss threshold returns of Omega and the target returns of reward-to-semi-variance are exogenously defined, which does not exactly reflect reality since they should be defined by investor's individual preference towards investment risk. Fifth, this study does not account for serial autocorrelation. For example, a positive autocorrelation biases the estimates of standard deviation of fund returns downwards, and therefore; for example, the Sharpe ratio yields over-optimistic results. And sixth, the methodology employed in this study, namely rank correlations and graphic presentations do not reveal causality between non-normality and fund performance. Regression analysis method is not employed due to the limited number of funds in each sub-sample.

1.5 Structure of the study

The first chapter of this study presented background and motivation for the topic of this thesis. In addition, the research problem, the limitations and contribution were also presented. Chapter 2 introduces the theory behind the topic, presents the performance measures employed and discusses the existing literature related to the topic. Chapter 3 describes the data and chapter 4 the methodology. Chapter 5 provides the empirical results of the study and chapter 6 summarises the findings and concludes.

2 THEORETICAL PORTFOLIO PERFORMANCE MEASUREMENT FRAMEWORKS AND PREVIOUS RESEARCH

This chapter provides an insight into the most relevant theoretical and empirical research relating to the performance measurement. Firstly, this thesis presents the traditional mean-variance framework and discusses two critical assumptions that justify it theoretically. Secondly, the following chapter presents the Sharpe ratio and discusses the alternative performance measures that have been introduced to capture the bias of the Sharpe ratio and the mean-variance framework in general. The final part of the chapter reviews some literature on the mutual fund performance evaluation.

2.1 Mean-variance framework

The father of modern portfolio theory is Harry Markowitz (1952), whose paper titled "Portfolio Selection" formalises the idea that a risk-averse investor faces a risk/reward trade-off for investor's investment decision problem. In this framework, the risk is defined as the variance (or standard deviation) and the reward is represented by the expected return of a portfolio. The formulation of Markowitz's portfolio problem can be written as follows:

$$Min \sum_{i,j=0}^{n} w_i w_j \sigma_{ij} \tag{1}$$

$$s.t. \sum_{i,j=0}^{n} w_{i,j} r_{i,j} = \bar{r} \tag{2}$$

$$and \sum_{i,j=0}^{n} w_{i,j} = 1, \tag{3}$$

where w_i = the weight of asset i in portfolio
w_j = the weight of asset j in portfolio
σ_{ij} = the covariance between the returns of asset i and j
r_i = the expected return of asset i
r_j = the expected return of asset j.

In this framework, asset allocation is performed by solving an optimisation problem. An investor chooses the level of expected return and forms an optimal portfolio with minimum variance or chooses the level of variance and maximises the expected return. Markowitz named this group of efficient portfolios "The Efficient Frontier". The efficient frontier exposes the trade-off between the expected return and risk: As an investor goes up the scale of expected return, he finds that risk is also increasing; and as he goes up the scale of riskiness, he finds that the expected rate of return is also going up at the same time. An investor chooses his preferred portfolio depending on individual risk preferences. An investor's risk preferences are depicted by a utility function, which, in this framework, is constrained to be only a function of the first two moments, namely mean and variance, of the portfolio return distribution.

The most essential contribution of Markowitz's work is his insistence on distinguishing the riskiness of an individual asset and the riskiness of an entire portfolio. The riskiness of a portfolio depends on the covariance of its holdings, not on the average riskiness of the separate investments. Although calculating Markowitz's rule was very difficult task for an investor in practise in the 1950s due to the absence of modern computers, it is still a very straightforward, and incomplete, formulation of portfolio selection problem. Nevertheless, the forthcoming literature developed the conditions necessary for this very simplified decision-making problem. In essence, the mean-variance framework is valid only if at least one of the following two assumptions holds:

1. An investor has a quadratic utility function
2. Portfolio returns are normally distributed.

The next two chapters introduce and discuss these assumptions that justify theoretically the mean-variance framework.

2.1.1 Quadratic utility function

Von Neumann and Morgenstern established their *Theory of Games and Economic Behaviour* in 1944. The paper introduces the idea that the decisions between different investments, or portfolio selection, are regarded as choices among alternative probability distributions of returns. The optimal choice is determined by maximisation of the expected value of an investor's utility function. Tobin (1958) shows that the mean-variance framework is consistent with the von Neumann-Morgenstern postulates of rational behavior if the utility function of wealth is quadratic[1]. The general form of quadratic utility function is formulated as follows:

$$U(W) = a + bW + cW^2 \qquad \text{with } a > 0 \text{ and } c < 0. \tag{4}$$

Further, the quadratic utility function has positive marginal utility and is strictly concave in wealth *(W)*. Therefore, the first two derivatives are written as follows:

$$U'(W) > 0 \qquad \forall\, W \tag{5}$$

$$U''(W) < 0 \qquad \forall\, W. \tag{6}$$

Equation 5 implies that an investor prefers more wealth to less. And, as noted above, in decision-making problem, an investor's objective is to maximise his utility function. Further, Equation 6 means that an investor exhibits dimishing marginal utility of wealth. An investor exhibiting this kind of utility function is called a risk-averse investor.

Although investor's utility functions may be highly complex and irregular in the real world, the quadratic utility function, which is indeed a very simplified form, is probably the most widely used criterion for optimal investment decisions. This fact may rather be attributable to testing concerns than actually to the persuasion that the quadratic form of utility function would be good instrument for an investor's economic behaviour in the real world. Actually, the quadratic utility function suffers form serious limitations.

First, Hanoch and Levy (1970) point out that when a second-order function is utilised in a portfolio selection problem, it is necessary to limit the range of possible outcomes beyond which it may not represent rational investor. This is due to the fact that any quadratic function has positive marginal utility only in a certain bounded range.

Second, the quadratic utility function and its strictly concave shape imply that the degree of risk aversion (ARA)[2] is everywhere increasing, which raises another

[1] The quadratic utility function leads to the Mean-Variance analysis being optimum. For detailed derivation see, for example, Elton and Gruber (1997a), p.220.

limitation. An increasing absolute risk aversion means that an investor holds less in absolute terms of money in risky assets as his or her wealth level increases. This argument has been heavily questioned by several researchers[3] and is inconsistent with the common experience of the real world behaviour of an investor. Empirical observations as well as theoretical considerations would actually lead one to assume *decreasing* absolute risk aversion.

In addition to ARA, the financial literature has presented a concept called relative risk aversion (RRA)[4], which measures the percentage change in investor's asset allocation in risky asset for some given wealth level. For example Blume and Friend (1975) exploit cross-sectional data on household asset holdings to assess the nature of households' utility functions. They report that the assumption of constant relative risk aversion and therefore, decreasing absolute risk aversion, depicts fairly accurately households' attitude towards risk.

Also, Cohn et al. (1975) examine investor's stance towards risk and base their study on questionnaire survey data, which consisted of 972 replies from investors who had at least one common stock transaction during seven-year period from January 1, 1964 to December 31, 1970. Although the questionnaire sought information on investment attitudes from investors with different demographic characteristics, the authors emphasise the sample is more heavily male, highly educated, wealthier, and older than the general US population. However, their data suggest a strong pattern of decreasing relative risk aversion: as wealth increases, a higher proportion of their total wealth is committed to risky assets. This result is in line with Huang and Litzenberger (1988) argument that if the quadratic utility function held, a risky asset would be an inferior good, which is also inconsistent with the behaviour of a rational investor.

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[2] Which is measured by Pratt-Arrow absolute risk aversion (ARA) and formulated as follows:

$$ARA(W) = \frac{-U''(W)}{U'(W)}.$$

[3] See, for example, Hicks (1962), Arrow (1963), Pratt (1964), Fellner (1965), Arditti (1967), Feldstein (1969), Hanoch and Levy (1970), Blume and Friend (1974), Cohn et al. (1975), Fishburn & Vickson (1978).

[4] Relative risk aversion is calculated: $RRA(W) = -W\frac{U''(W)}{U'(W)}$.

However, despite the heavy empirical evidence against the quadratic utility function, let us concentrate on its implications for portfolio selection. Assuming that the quadratic utility function is a valid instrument for depicting an investor's economic behaviour, his expected utility is only a function of the first two moments of the portfolio return distribution. Thus, mean and variance are sufficient to solve the maximisation problem even though returns are not normally distributed. The focus on the variance as an appropriate measure of risk implies that investors weigh the probability of below-the-mean and above-the-mean returns equally. However, it is very unlikely that investors' perception of downside risk is the same as the perception of upside potential. Recent behavioural finance literature[5] has reported some evidence that investors weigh losses more heavily than gains, and therefore it is proposed, all over again, that the quadratic utility function should be abandoned.

2.1.2 Normally distributed returns

After rejecting the assumption of the quadratic utility function, there is another way to justify the mean-variance framework, namely normally distributed returns. When asset returns are normally distributed, the mean and the variance fully capture risk and reward characteristics of a distribution. The density function of the standard normal distribution is computed as follows:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \tag{7}$$

where μ = the mean of the probability distribution

σ = the standard deviation of the probability distribution.

We can observe from the Equation (7) that the distribution is fully defined by the mean and the standard deviation. The density function of the normal distribution is often referred as the Gaussian distribution[6] or the bell-shaped curve.

[5] See, for example, Bernartzi and Thaler (1995) and Siegmann and Lucas (2002).

[6] The normal distribution is a mathematical construction attributed to a German mathematician called Karl Friedrich Gauss.

As the first two moments of a distribution are mean and variance, the third one is called skewness. Skewness is a measure of asymmetry of a distribution. A symmetric distribution has zero skewness, an asymmetric distribution with the largest tail to the right has positive skewness, and a distribution with a longer left tail has negative skewness. For example, the normal distribution has zero skewness: the shape of the distribution above the mean is a mirror image of the shape below the mean. In an economic sense positive skewness expresses upside potential for an investment.
Skewness is estimated as:

$$skewness = \frac{n}{(n-1)(n-2)} \sum \frac{r_i - \overline{r_i}}{s} \tag{8}$$

where n = the number of observations

r_i = the return of asset i

$\overline{r_i}$ = the average of return of asset i

s = the sample standard deviation.

The fourth central moment of a distribution is kurtosis. There is no consensus of opinions what it really measures. Commonly it is argued that kurtosis a measure of peakedness, but strictly speaking it measures both peakedness and tail heaviness of a distribution relative to that of the normal distribution. Accordingly, this implies that a distribution exhibiting positive excess kurtosis has both higher probability mass around the mean and higher probability mass in tails than the normal distribution. As the kurtosis of the standard normal distribution is three, the excess kurtosis is estimated as:

$$Excess\ kurtosis = \left\{ \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum \left(\frac{r_i - \overline{r_i}}{s} \right)^4 \right\} - \frac{3(n-1)^2}{(n-2)(n-3)} \tag{9}$$

And so, the standard normal distribution has excess kurtosis of zero.

In an economic sense, high kurtosis implies that the probability of extreme outcomes, i.e. the probability of great losses or gains, is higher than when kurtosis is lower. This phenomenon relates to the problem, which has occupied both academics and practitioners in recent years, namely the fat-tailed financial returns.

In fact, a great number of studies report that the distributions of financial assets are not normally distributed. The financial literature has traditionally concentrated on the normality of return distributions of individual securities. Mandebrot (1963), Fama (1965), Arditti (1967, 1971), Praetz (1972) and Simkowitz and Beedles (1978) published the first studies addressing the non-normality of returns of individual securities. They all find evidence on skewness and excess kurtosis (i.e. leptokurtosis) of empirical return distributions. In addition, they all propose different statistical distributions for price chances of financial assets. All the proposed distributions have, however, same characteristics between themselves: they are more peaked and exhibit fatter tails than the Gaussian distribution[7].

A number of more recent studies also document strong evidence on non-normality of financial returns. For example, Peiro (1999) carries out tests of symmetry of daily returns for nine international stock market indexes[8] and three spot exchange rates[9]. His data consist of observations of one-day returns from January, 1980 to September, 1993. He reports that the assumption of symmetrical returns is rejected in eight of the nine time series of stock returns and in all cases of the three spot exchange rates. Interestingly, the author points out that as the stock series are stock index returns, the results really refer to portfolio returns, because the indexes can be seen as well-diversified portfolios of each market.

In addition, Aparicio and Estrada (2001) study European Stock market data, which include Finland as well, and conclude that daily stock returns are not normally distributed. Further, they find that the distributions of daily stock returns exhibit fat-tails and high peaks, as well as both positive and negative skewnesses. However, their tests

[7] For example, the student t-distribution with suitable degrees of freedom is widely used in modeling financial returns, since it has fatter tails than the normal distribution.
[8] The stock indexes are S&P 500, Dow-Jones Industrial, Nikkei, FT 100, Commerzbank, CAC General, Composite, Banca Commerciale Italiana and General.
[9] The exchange rates are the Japanese Yen vs. the US Dollar, the British pound vs. the US Dollar and the German Mark vs. the US Dollar.

do not find any evidence that monthly stock returns would significantly deviate from normal distribution, but they assert the normal distribution may significantly underestimate the risk of investing in European stocks.

Vaihekoski (1997) examines the predictability of the Finnish asset returns using daily, weekly, and monthly data from 1987 to 1995. In his paper the market portfolio return is proxied by the return of the HEX-index (prior to 1990 the WI-index is used instead). Vaihekoski reports that the return distributions are non-normal for the daily and weekly market returns, but for the monthly market returns his hypothesis of normal distribution cannot be rejected. This result is in line with the earlier studies reporting that asset returns show decreasing non-normality when the observation interval increases.

Although the non-normality of individual asset returns has been frequently reported in number of studies, the relationship between individual asset returns and portfolio returns is not that straightforward. For example, Levy and Markowitz (1979) and Kroll, Levy and Markowitz (1984) defend the use of the quadratic utility function and the mean-variance analysis. In essence, they argue that while the individual stock return distributions are non-normal, the optimal diversified portfolios will be very close to a normal distribution. On the other hand, Osband (2002) points out that the diversification may have an adverse effect as well: for example a portfolio of high-yield bonds, each with very fat-tails individually, can be normally distributed in aggregate, while assets without almost any tail risk can cause a very fat-tailed portfolio if they all are vulnerable to the same risk[10]. As my sample covers equity, bond, asset allocation, risk and hedge funds, these are fundamental findings for this study. In addition, this study separates also equity funds according to their geographical orientation.

Further, the several scholars have also examined the non-normality of hedge fund returns. For example Favre and Galeano (2001), Berényi (2002), Amin and Kat (2001) and Favre-Bulle and Pache (2002) find that hedge fund returns deviate strongly from

[10] As the Central Limit Theorem states that the sum of identically and independently distributed (i.i.d.) variables (with finite variances) converges to the normal distribution, Osband (2000) argument seems at first sight to violate it. However, it should be noted that asset returns may not be independently distributed.

normality[11]. Hence, they define investment risk with a measure including not only the variance but also skewness and excess kurtosis implying that negative skewness and positive excess kurtosis increase the risk of a distribution. This approach is also exploited in this study and introduced in the following chapters.

The only Finnish study on non-normality of mutual fund returns is Asikainen (2002) master's thesis, which examines the validity of the Sharpe Ratio and the mean-variance framework. His empirical data consist of daily returns of 121 mutual funds that are marketed in Finland between 1999 and 2001. He conducts Jarque-Bera tests for the total sample (n=121) and for two different sub-samples: equity funds (n=81) and equity funds that are registered in Finland (n=54). He reports negative skewnesses throughout the total sample during the whole time period across all the sub-samples. For individual funds skewness values in the bearish 2001 and 2000 are more negative than in the bullish 1999. In addition, the paper shows strong evidence on excess kurtosis concerning individual funds: the highest in 1999, the lowest in 2001. As a consequence, during the whole sample period 1999-2001 none of the 121 funds is normally distributed and during each separate year the majority of the mutual funds deviate from the normal distribution.

The empirical evidence supporting the assumption of non-normally distributed fund returns is very interesting especially if it is considered in light of Samuelson (1970), Levy and Markowitz (1979) and Kroll, Levy and Markowitz (1984) argument that non-normality, skewness in particular, can be diversified away in well diversified portfolios. However, as stated earlier, Asikainen (2002) reports persistent negative skewness in the returns of mutual funds marketed Finland in each separate year during 1999-2001. Accordingly, it is possible that portfolio managers may have intentionally exploited non-normal investment strategies during those years. Furthermore, if this truly is the case, we can justifiably assume that the mean-variance framework may not be sufficient for evaluating the performance and the riskiness of Finnish mutual funds.

[11] The reader should note that hedge fund portfolios can include various non-linear instruments, and therefore their return distributions may drastically be different from the return distributions of traditional asset classes.

A recent paper by Driessen and Maenhout (2004) sheds light on this phenomenon. Driessen and Maenhout study the standard asset allocation problem when investors have access to index options. They argue that investors[12], regardless of the level of their risk-aversion, always find it optimal to short out-of-the-money (OTM) put options and at-the-money (ATM) straddles. One might intuitively think that when a risk investor has a long position in an equity index, he would choose a protective-put strategy, i.e. long put position on the index. Nevertheless, this is not the case. Actually, the optimal strategy is to short both the equity index and the OTM put option. This, in turn, results from the widely documented anomaly of excessively high priced OTM put options[13]. In fact, Driessen and Maenhout (2004) argue that investor should *never* have positive demand for OTM put options given those observed high prices.

For example, concentrating on the payout profile of an OTM put option we find an interesting fact for this study. The return distributions of long and short positions in an OTM put option are not symmetric in shape. A short OTM put is highly skewed to the left implying that most of the time the writer (i.e. the one with short position) collects a moderate profit. At the same time the buyer (i.e. the one with long position) suffers a moderate loss. On the other hand, once in the while the writer takes a big loss, whilst the buyer gains a lot. Therefore, in a statistical sense, short (long) position in an OTM put exhibits a negative (positive) skewness value. In fact, Driessen and Manhout (2004) report highly negative skewness values of -5.452 and -10.458 for short 0.96[14] and 0.92 OTM put options, respectively. Further, it has been shown that shorting has actually been extremely profitable strategy historically. From this point of view, the Scott and Hovath (1980) argument that an investor desires high positive skewness does not seem to hold due to the anomalous high prices of OTM puts.

2.2 Composite performance measures

It is widely accepted view that Markowitz's portfolio theory has laid the foundation for modern portfolio performance evaluation. Prior to this, mutual funds had been evaluated

[12] To be specific, constant relative risk averse investors.
[13] See for example, Jones (2001) and Bondarenko (2003a, 2003b). The anomaly is often referred as "overpriced puts puzzle".
[14] The ratio reflects the "moneyness" of an option defined as a strike-to-spot ratio. A put option with a strike-to-spot ratio of less than one is an out-of-the-money option.

based only on raw returns. For example Cowles (1933) compared the returns of a set of managed portfolios to a passive portfolio, but ignored any consideration of risk. It was Markowitz's modern theory, which taught that investors and fund managers need to be concerned with risk as well as returns in analysing performance. His path-breaking contribution enabled Sharpe (1964), Lintner (1965), and Mossin (1966) to develop the most famous financial equilibrium model: the Capital Asset Pricing Model (CAPM). However, their model demands a very strict assumption, namely there are no market frictions. In particular, there are no transaction fees, investors can shortsell without restrictions, and they can borrow and lend at the risk-free rate without limitations. Although the first versions of CAPM were developed in a static, single-period setting, it triggered later many inter-temporal, multi-period versions[15].

Further, it did not take too long when the first methods for modern portfolio evaluation were introduced which used the recent insights from the CAPM. The Sharpe (1966), Treynor (1965) ratios, and the Jensen (1968, 1969) alpha are the first single-parameter measures for adjusting the fund returns for risk. These three early studies can be seen as the foundation for many modern fund evaluation techniques, and the measures of Treynor (1965) and Sharpe (1966) are nowadays mostly used among practitioners but the Jensen (1968, 1969) measure is still widely used both by scholars and practitioners. This study concentrates on the Sharpe ratio and its more developed forms in a single-period setting.

2.2.1 Sharpe ratio

Sharpe introduced probably the most famous measure for portfolio performance evaluation in 1966. He examined 34 mutual funds during the time period 1954-1963. In addition, Jensen introduced his measure in 1968 and evaluated 115 mutual funds during the time period 1945-1964. They both find that the funds have underperformed their relevant benchmark. Nonetheless, the Sharpe ratio relies on Markowitz's mean-variance paradigm, which assumes that the mean and the standard deviation of the distribution of one-period returns are sufficient statistics for evaluating the performance of an investment portfolio (Sharpe 1994). The ratio ranks portfolios based on their efficiency

[15] See Fama (1970), Hakansson (1970, 1974), Merton (1990) and Mossin (1969).

to earn excess returns against the risk[16] implying that better portfolios get higher values. More closely, the *ex post* or historic Sharpe ratio is calculated using mean and standard deviation of differential return D_t as follows:

$$D_t = r_{pt} - r_{bt} \tag{10}$$

where r_{pt} = the return of the portfolio p in period t

r_{bt} = the return on the benchmark portfolio or index in period t.

Further, the average of D_t over the historic period from t=1 through T is denoted by $\overline{D}$:

$$\overline{D} = \frac{1}{T}\sum_{t=1}^{T} D_t \tag{11}$$

and the standard deviation over the period by σ_D :

$$\sigma_D = \sqrt{\frac{\sum_{t=1}^{T}\left(D_t - \overline{D}\right)^2}{T-1}} \tag{12}$$

Therefore, the *ex post* Sharpe ratio is:

$$Sharpe = \frac{\overline{D}}{\sigma_D} \qquad \text{(Sharpe 1994).} \tag{13}$$

The Sharpe ratio can be expressed also as:

$$Sharpe = \frac{\overline{r_{pt}} - \overline{r_{bt}}}{\sigma_D}, \tag{14}$$

[16] In the mean-variance framework investment risk is proxied by standard deviation.

which is equivalent to the Equation (13). This formulation of the Sharpe ratio is henceforth used in this study.

The Sharpe ratio expresses the slope in excess return and standard deviation universe. Further, as standard deviation depicts total (i.e. both systematic and unsystematic) risk, it can be stated that the ratio expresses the slope in excess return and total risk universe. The ratio is feasible when the fund under evaluation represents the investor's entire investment portfolio. Further, Sharpe (1994) explains that the excess return represents the result of a zero-investment strategy. In essence, the excess return expresses a self-financing investment portfolio: in the numerator of Equation (14) the first component $\overline{r_{pt}}$ represents the acquired asset (the fund) and the second component $\overline{r_{bt}}$ reflects the short position taken in another (the benchmark) to finance the acquisition. The benchmark return was originally to be a risk-free security, but more recent applications have utilised benchmark portfolios representing investment style similar to that of the fund being evaluated. Therefore, this differential expresses the difference between the return on the fund and the return that would have been obtained from a "similar" passive alternative. In this case Sharpe terms the differential return an "active return" or "selection return".

However, the literature has criticised extensively the mean-variance framework and the Sharpe ratio as comprehensive portfolio evaluation measure. Firstly, the Sharpe ratio suffers from widely cited Roll (1978) critique which states that performance measures related to the security market line of the CAPM are sensitive to the empirical proxies for the market portfolio.

Secondly, one of the most commonly adduced weaknesses of the Sharpe Ratio relates to its dependence of the observation period (Sharpe 1994). For example, referring to Pätäri (2000), assume that Sharpe ratios for two successive years are equal when the length of the observation period is one year. When the time span of evaluation period is extended to cover both years, i.e. in that case there is only one observation period, the value of ratio may differ radically from the case mentioned above: It can easily change from outperformance to underperformance. The bias of this kind to the value of the ratio can arise due to changes in investment policy[17]. In the portfolio performance evaluation context the bias may arise, if a portfolio manager changes the portfolio composition since the Sharpe approach assumes constancy of risk over time. Also, as noted by Kahn (1996) it cannot identify a new fund manager, new assets, or changing levels of market volatility. Note that all the results in this study are subject to this critique particularly.

Thirdly, the ratio has been criticised, because it is mean-dependent. According to Pätäri (2000) risk may not be a uniform concept: what is regarded as risky for one return distribution may not be that for another. Therefore, risk is not mean- or expected value-dependent concept, but rather bonded individually to the target return, under which an investor does not wish to end up.

Fourth criticism is called the reversal rank order pointed out first by Jobson and Korkie (1981). They show that when the expected return of portfolio is lower than the risk-free rate (or the benchmark index), the Sharpe Ratio does not function appropriately as a performance measure: If two assets have equal negative excess returns, the one with higher volatility yields less negative, i.e. higher value. As a consequence, the Sharpe ratio indicates that the more volatile asset is superior to the other asset. Therefore, it is clear that if assets have negative excess returns, the Sharpe Ratio yields meaningless results.

And finally, several authors[18] have shown that Sharpe ratio is inapplicable if investors possess market timing ability. An investor with a superior information set causes shifts in efficient portfolio composition resulting return distribution to be non-normal. It is noteworthy; however, that this may not be a fundamental issue since plenty of empirical evidence has shown that if market timing ability exists at all, it is very rare. Further, the finding is not that relevant in the context of this study as I am examining particularly the effect of higher distributional moments on performance and risk measurement.

In addition to these theoretical flaws, there are some empirical problems with the Sharpe ratio. First and most importantly, as reported in section 2.1.2, several studies document

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[17] See Bodie et al. (1989), p.735-737.

[18] See, for example, Henriksson (1984) and Lehman and Modest (1987).

that asset returns are not normally distributed. Second, the vast financial literature[19] suggests that investors concern differently towards downside deviation and upside potential, i.e. they weigh more losses than gains. For all these reasons, it is suggested that the mean-variance framework, or the Sharpe ratio, does not appropriately capture risk and reward properties of asset returns, and alternative methods capturing its bias have been introduced.

2.2.2 Reward-to-semi-variance

An alternative formulation of investment decision problem uses downside deviation as a measure of risk. Downside deviation is an asymmetric measure of risk that focuses only on the returns below specific return target. Roy's The Safety First Criterion in 1952 can be seen as a pioneering paper in measuring risk with downside risk approach. Roy argues that the optimal decision for an investor is to choose the portfolio with the smallest probability of producing a return below some specified level. Roy calls this minimum acceptable return as the disaster level. According to, for example, Nawrocki (1999) Roy's concept of an investor preferring safety of principal first when dealing with risk is instrumental in the development of downside risk measures.

Also, Markowitz (1959) discusses quantifying investment risk with the downside risk approach. He finds out that only downside risk relevant to an investor and admits that security return distributions may not be normally distributed. He proposed two suggestions for measuring downside risk: a semi-variance computed from the mean (below-mean semi-variance) and a semi-variance computed from a target return (below-target semi-variance). In fact, Markowitz states that "the semi-deviation produces efficient portfolios somewhat preferable to those of the standard deviation". So, below-target semi-variance is exploited in this study and estimated as follows:

$$\text{Below-target semi-variance (SVt)} = \frac{1}{n}\sum_{t=1}^{n}\left[\min(r_{pi} - \tau, 0)\right]^2 , \qquad (15)$$

[19] See for example Quirk and Saposnik (1962), Mao (1970), Klemkosky (1973), Bawa (1975), Fishburn (1977) and Ang and Chua (1979).

where r_i = the return of portfolio p

τ = the return target

n = the number of outcomes in the whole distribution.

It should be pointed out that investment risk is defined otherwise here than in the context of mean-variance framework. Whereas the semi-variance is estimated from the *gross return* distribution of a portfolio, the standard deviation of the Sharpe ratio is estimated from the *excess return* distribution of a portfolio. Further, contrary to the mean-variance framework, in which the investment risk originates from the total deviation of excess return, the investment risk arises in the semi-variance framework from not achieving the target return. Actually, the standard deviation of the Sharpe ratio is often misleadingly estimated from the gross return distribution. However, as stressed by Sharpe (1994) the standard deviation must be estimated form excess return, or else the ratio loses its original meaning, i.e. representing return and risk characteristics of a zero-investment strategy. Thus, the Sharpe ratio is estimated as presented in Equation (14), in other words using standard deviation calculated from excess returns.

Nevertheless, defining risk as outcomes below the target return is in line with studies by, for example, Clarkson (1990), Miller and Reuer (1996) and Olsen (1997). In addition, many researchers[20] have discussed the superiority of semi-variance (or downside deviation) versus variance in the context of portfolio selection, but only a few studies discussing the impact of the advances in the alternative risk quantification on performance measurement have been published. However, studies by Klemkosky (1973) and Ang and Chua (1979) show that performance measures dependent on normal distribution could provide incorrect rankings and suggest the reward-to-semi-variability ratio (R/SV) as an alternative[21]. On the other hand, they report that semi-variance suffers from poor statistical properties. Nonetheless, the *ex post* reward-to-semi-variance by Klemkosky (1979) is estimated as:

[20] See for example Quirk and Saposnik (1962), Mao (1970), Sortino and Price (1994), Evensky (1996), Pedersen and Satchell (1998), Grinold (1999), Grootveld and Hallerbach (1999), Kochmann (1999), Leland (1999), Nawrocki (1999), Ogryczak and Ruszczynski (1999), Pownal and Koedijk (1999), Eftekhari et al. (2000) and Israelsen (2000).

[21] All these terms can be confusing since different researchers use different names for the same concepts: for example, R/SV is really the return to below-target semi-deviation ratio, which, in turn, is also referred as the Sortino ratio [see Sortino and Price (1994)].

$$Reward\text{-}to\text{-}semi\text{-}variance\ (R/SV) = \frac{\overline{r_p} - \overline{r_b}}{\sqrt{SVt}}. \qquad (16)$$

Note that the R/SV does not base on any theoretical framework, but still its proponents argue that the R/SV is superior to the Sharpe ratio. Unlike variance or standard deviation, downside deviation does not increase with greater upside potential. As a consequence, it has been widely reported that variance, and therefore the Sharpe ratio, overestimates the risk of an investment. Thus, downside deviation is a more robust tool for risk quantification and performance measurement. Hence, using downside deviation the information contained in the upside of the distribution does not contribute to the risk but is captured in the mean of the distribution.

When calculating the R/SV, the return target is set according to investor's risk aversion to returns below a specific benchmark level: the higher the return target, the more risk-averse investor. According to Sortino and Price (1994) the mean-downside deviation framework is more aligned with observed investors' perception of returns distribution, for which losses weigh more than gains. In addition, Favre-Bulle and Pache (2002) state that the mean-semi-variance framework uses less restrictive assumptions than the mean-variance framework. It only requires general assumptions with respect to investor's utility function, namely risk-aversion and preference for skewness. As mentioned before, positive (negative) skewness is traditionally considered as a favourable (unfavourable) property for a distribution. And more generally, Scott and Horvath (1980) argue that investors desire high odd moments and low even moments.

2.2.3 Value-at-Risk modified Sharpe ratio

In recent years there has been huge interest towards another downside risk measure, a concept called Value-at-Risk (VaR). It was first introduced by Baumol (1963), but the use of it exploded in 1996 when The Basle Committee on Banking Supervision proposed allowing banks to calculate their capital requirements for market risk with their own value at risk models, using parameters provided by the committee (Linsmeier and Pearson 1996). Also, in year 1995 the US Securities and Exchange Commission enabled the US companies to disclose their market risk exposures using VaR as one of three possible methods. As a consequence, VaR has become the standard measure that financial analysts use to quantify risk. Nowadays it has many applications, such as in risk management, for regulatory requirements and, what is of interest in this study, to evaluate the performance of risk takers [Manganelli and Engel (2001)].

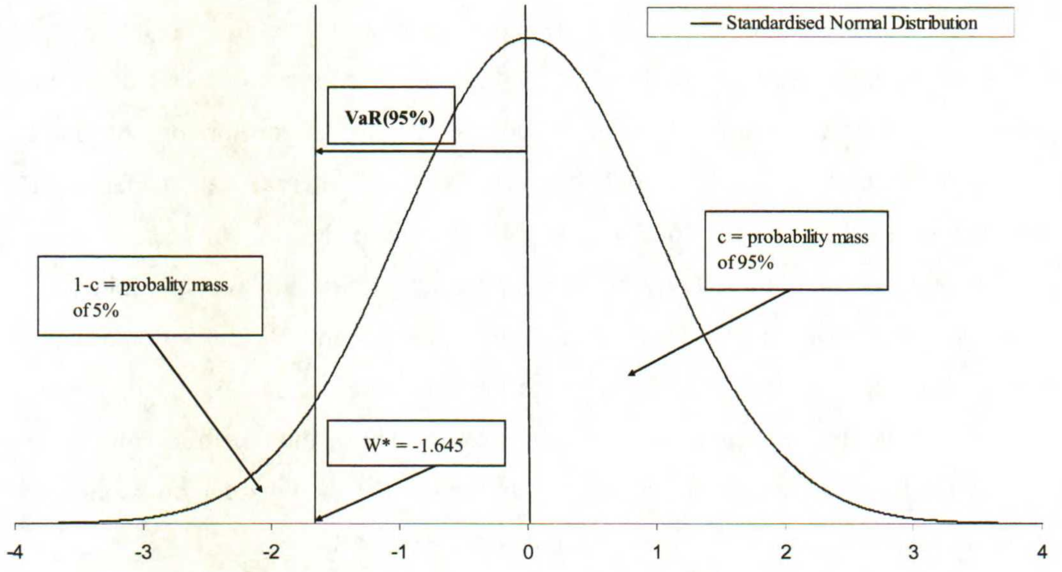
Jorion (2000) defines Value-at-Risk as a measure that summarises the maximum loss over a target horizon with a given level of confidence. More formally, VaR describes the quantile of the distribution of gains and losses over the target horizon. As noted earlier, VaR is used for banks' regulatory reporting and internal risk management purposes, and calculated mostly for 95% and 99% confidence levels. The target horizon selected should correspond the horizon needed a bank to adjust the level of capital, i.e. to raise additional equity. If the bank suffers a loss greater than the VaR within a target horizon, its equity is wiped out, and the bank defaults [(Jorion (2000)]. In its general form, VaR can be derived from the probability distribution of the portfolio value $f(w)$. At a given confidence level c, we find the maximum loss W^* such that the probability of value lower than W^*, $P(w \leq W^*)$, is $1 - c$ and determined as follows:

$$1 - c = \int_{-\infty}^{W^*} f(w)dw = P(w \leq W^*). \qquad (17)$$

In other words, the area from $-\infty$ to W^* in the probability distribution sums up to $P(w \leq W^*) = 1 - c$, for example, 5 per cent. A graphic illustration of $\mathrm{VaR}_{95\%}$ using standard normal distribution is presented in Figure 1.

Figure 1 $VaR_{95\%}$ and Standardised Normal Distribution

This figure exhibits the Value at Risk (VaR) figure estimated from the standardized normal distribution at 95% confidence level. The portfolio value is depicted on the horizontal axis and the maximum loss selected is denoted by W^*, which is -1.645 here. The probability of value lower than W^* is $1-c$, which in this case is 5%. The probability of value higher than W^* is c, which denotes the confidence level chosen and is 95%. VaR (95%) is the distance from the mean of the distribution to the W^*, which is -1.645 and corresponds to the maximum loss over a target horizon at 95% confidence level.



Arzac and Bawa (1977), Huismann, Koedijk and Pownall (1999) introduce a portfolio optimisation model, which allocates assets by maximising the expected return subject to the constraint that the probable maximum loss meets the investor's VaR limit. In the framework, the risk is defined as the VaR relative to a benchmark return (for example risk-free rate). The authors argue that the mean-VaR approach fits with the investor's behaviour of minimising the exposure to large losses. The degree of risk-aversion is reflected in the chosen VaR level and the associated confidence level. Broadly, the optimisation process is similar to that of mean-variance approach except for the definition of risk. [Favre-Bulle and Pache (2002)]

The main benefit of the mean-VaR approach is that using empirical returns distributions optimal allocation does not require any assumption regarding the shape of the distribution. However, Dowd (1998) emphasises that the choice of the sampling period and the reliance on a large sample are essential in order to estimate the quantiles accurately. This observation raises problems when assessing empirical returns if the data selected are scarce and low frequented. So, although the general statistical properties of mutual fund returns are examined using daily, weekly and monthly observations (section 5.1), in order to attain reliable results for evaluating the risk-adjusted fund performance the monthly returns are excluded in the following sub-chapters (5.4 – 5.7).

However, the *ex post* VaR is estimated assuming normally distributed returns[22]. Hence, it is formula can be presented:

$$VaR_{(c)} = \left(\overline{r_p} - z_c \sigma_p\right) W, \tag{18}$$

where c = the confidence level

$\overline{r_p}$ = the average return of portfolio p

z_c = the critical value of the normal standard distribution at a *(c)* threshold

σ_p = the standard deviation of the return distribution of portfolio p

W = the size of the investment.

Following Favre-Bulle and Pache (2002) the estimation of VaR over short period is customary to perform assuming that the rate of return is zero. As I work with daily and weekly data, I do not include the mean return into the calculations. Further, it can also be noted that the size of the investment W does not affect performance measurement. Thus, its value is set to one. Finally, as I am considering losses only, I take the absolute value of VaR. Therefore, assuming normally distributed returns, the $VaR_{99\%}$ in this study is estimated as follows:

$$VaR_{99\%} = \left|-2.326 * \sigma_p\right| \tag{19}$$

and $VaR_{95\%}$ as:

$$VaR_{95\%} = \left|-1.645 * \sigma_p\right|, \tag{20}$$

where $\overline{r_p}$ is set to zero and W is set to one.

[22] The student t-distribution is widely used in VaR modelling as well.

Further, as the impact of the mean return is usually low and thus set to zero in this study, it is noteworthy that VaR is essentially a multiple of the standard deviation. As a consequence, under the assumption of normally distributed returns, the mean-variance and the mean-VaR frameworks lead to almost identical results, but they suffer from the very same weaknesses. In addition, Dowd (1998) argues that the mean-VaR analysis biased to safe positions when normality is assumed. He discusses the risk of a large market move, such as a market crash. He asserts that market returns often show fat tails, which indicates that large losses are more likely than would be implied by normality. Reliance on normal-based measures can therefore lead to drastic underestimates of the "true" VaR.

To overcome this problem, the literature has introduced several different models [see, for example, Koedijk and Pownall (1999), Lhabitnat (2001)]. However, this study utilises a model proposed by Favre and Galeano (2000), in which VaR is adjusted for the third and fourth moments of a return distribution, namely skewness and kurtosis, respectively. I adjust the critical value of the normal distribution for skewness and kurtosis by using the Cornish-Fisher expansion:

$$z_{CF} = z_c + \frac{1}{6}(z_c^2 - 1)S + \frac{1}{24}(z_c^3 - 3z_c)K - \frac{1}{36}(2z_c^3 - 5z_c)S^2, \qquad (21)$$

where z_c = the critical value of the normal distribution at a *(1-c)* threshold

S = the skewness of the return distribution

K = the excess kurtosis of the return distribution.

Hence, the one-day 99% CFVaR is calculated:

$$CFVaR_{99\%} = \left| - z_{CF} * \sigma_p \right|. \qquad (22)$$

And for the performance measurement context, the investor faces the same risk-reward trade-off as earlier, but it is described, first, in terms of VaR and historical excess return:

$$VaR\ Modified\ Sharpe = \frac{\overline{r_p} - \overline{r_b}}{\overline{r_b} - VaR_{99\%}}. \qquad (23)$$

Second, in terms of CFVaR and historical excess return:

$$CFVaR\ Modified\ Sharpe = \frac{\overline{r_p} - \overline{r_b}}{\overline{r_b} - CFVaR_{99\%}}. \tag{24}$$

The VaR Modified Sharpe ratio (VaR Sharpe) assumes normality and incorporates only the first two moments of the returns distribution. In addition to the mean and the variance (or standard deviation), the CFVaR Modified Sharpe ratio (CFVaR Sharpe) embodies the third (skewness) and the fourth (kurtosis) moments as well. However, it has been argued that investors care about all the moments in a return distribution. Accordingly, it has been suggested that this framework either may not adequately characterise the risk/reward properties of non-normally distributed returns.

2.2.4 New technique: Omega

Keating and Shadwick (2002a, 2002b) introduce a new performance evaluation measure, Omega, which embodies all of the moments of a return distribution. The authors argue that Omega provides a full characterisation of risk and reward properties of a return distribution. Instead of estimating any individual moments of the distribution, Omega measures their total impact on performance, which, according to the authors, should be in the interest of investors and portfolio managers. In fact, they assert that it is extremely difficult to establish that an effect is caused by some individual moment, which suggests very strongly that any approach which depends on systematically extending econometric analysis based on individual moments is doomed to fail.

Further, Omega provides a risk and reward evaluation measure derived directly from a return distribution which incorporates the beneficial impact of gains as well as the detrimental effect of losses, relatively to any investor's individual loss threshold. The evaluation statistics Omega has a precise mathematical definition as:

$$\Omega(r) = \frac{I_2(r)}{I_1(r)}, \tag{25}$$

where $$I_1(r) = \int_a^r F(x)dx \tag{26}$$

and

$$I_2(r) = \int_r^b (1 - F(x))dx, \tag{27}$$

where F = the cumulative distribution of the asset returns on the interval $[a,b]$

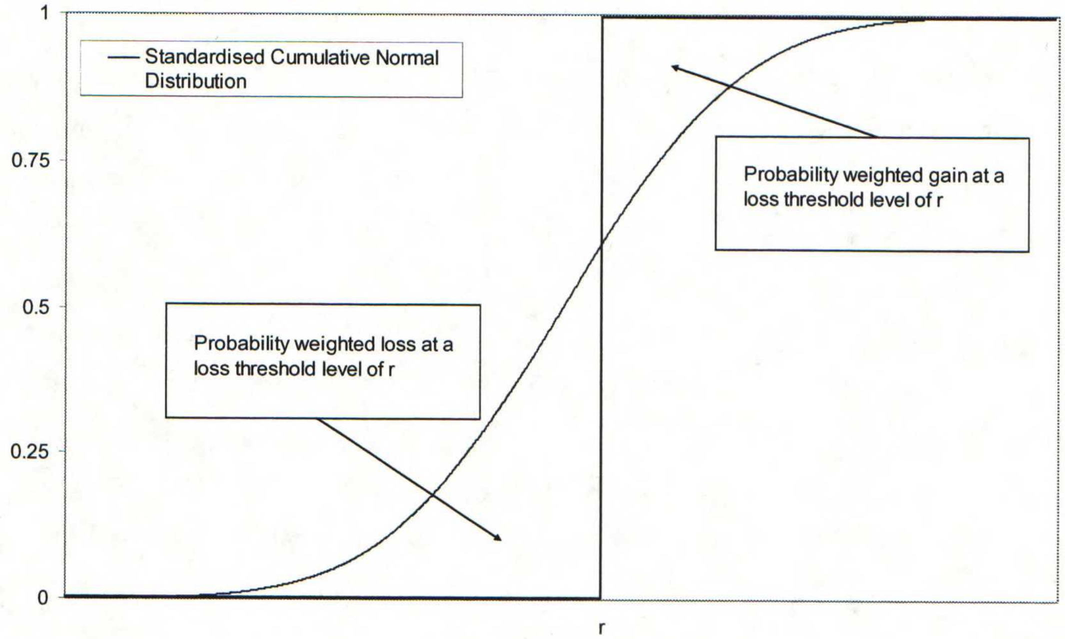
r = the return level regarded a loss threshold.

For any investor, returns below his specific loss threshold are considered losses and returns above gains. Accordingly, Farinelli and Tibiletti (2002) simply assign Omega as a ratio between the favourable events and the unfavourable ones. At a fixed loss threshold b, the higher value of Omega is preferred to a lower value.

Figure 2 exhibits the determinants of the Omega function using the standardised cumulative normal distribution. The probability of the favourable events, i.e. gains, is the area above the graph and to the right of the loss threshold r. The probability of the unfavourable events, i.e. losses, is the area under the graph and to the left of the loss threshold r. Note that the higher the loss threshold, the more risk averse investor.

Figure 2 Determinants of Omega function

This figure presents the standardised cumulative normal distribution and the determinants of Omega function. The loss threshold level is at *r*. The denominator of Omega function, the probability weighted loss (I_1) is the area under the graph and to the left of *r*. The numerator of Omega function, the probability weighted gain (I_2) is the area above the graph and to the right of *r*. For any threshold return level *r*, the number of Omega is the probability weighted ratio of gains to losses, relative to the threshold *r*. Therefore, a higher Omega value is preferred to a lower value. If the loss threshold *r* is set to the mean of any return distribution, Omega gets the value one.



Keating and Shadwick (2002a) argue that Omega is, in a mathematically sense, equivalent to the returns distribution itself embodying all of its moments. This implies that while the traditional mean-variance approaches rely on approximation of normality, Omega is, in rigorous mathematical sense, equivalent to a return distribution itself. Further, as Omega is a function that can be evaluated at any value in the range of possible returns, it provides a ranking rule for comparable assets with respect to any risk threshold in this range. Furthermore, Omega requires no assumptions about risk preferences or specification of an investor's utility function for performance ranking. In order to rank, for example, portfolios we need only to assume that an investor prefers more money to less money (i.e. non-satiation).

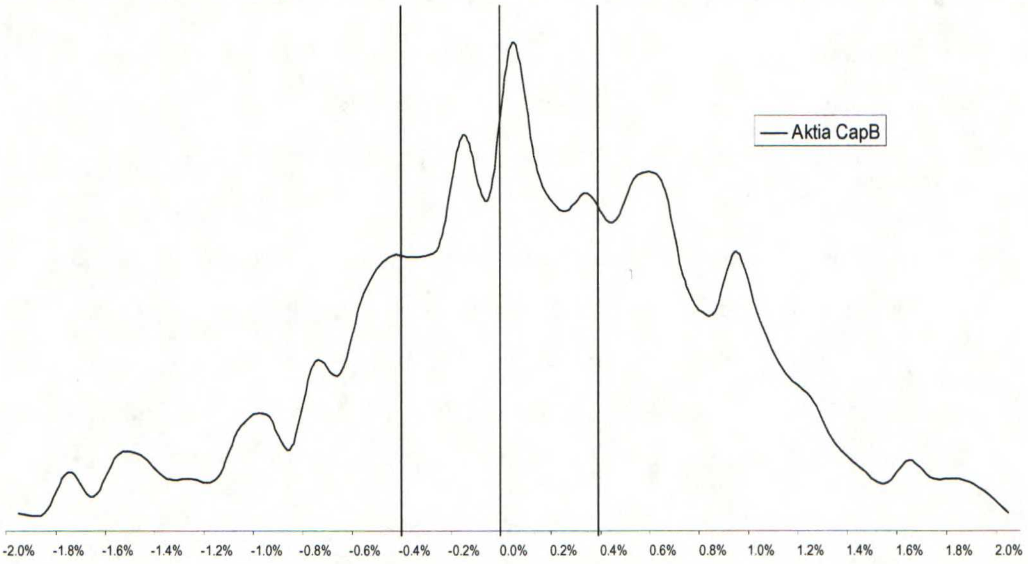
The absence of a utility function here may, at first sight, be disconcerting. However, in order to *rank* portfolios over an interval of possible returns, all that is needed is a comparison of the magnitudes of their Omegas over that interval. For example, if asset A's Omega is larger than asset B's over an interval, we should prefer asset A in that range of returns. If we wish to quantify the difference between the two assets on the other hand, we must introduce an additional structure which can, for example, decide how much better Omega of 2 is than Omega of 1.5. A utility function is the obvious way to do this. [Keating and Shadwick (2002a)]

Keating and Shadwick (2002a) show that in addition to providing corrections to the mean-variance measures by taking higher moment information into account, Omega also takes into account the level of return against which a given outcome will be viewed as a gain or loss. So, even if returns are normally distributed, Omega should provide additional information, which the mean-variance measures do not encode. Hence, different benchmark levels can lead to significantly different portfolio optimisations and performance rankings that are produced by the traditional performance evaluation techniques. However, forming optimal portfolios is beyond the scope of this study and it is hence excluded from this study. This paper focuses on performance measurement only. In addition, the Sharpe ratio, the R/SV, the VaR Sharpe and the CFVaR Sharpe are referred henceforth as "the traditional performance measures" as distinct from Omega.

Figure 3 shows the return distribution of Aktia Capital in 1999-2003. In addition, three different loss threshold levels of -0.4%, 0.0% and 0.4% are illustrated. The loss thresholds in this study are defined exogenously, which does not exactly reflect reality since they should be defined by investor's individual preference towards investment risk. Nevertheless, the attractiveness of the fund clearly depends on the loss threshold level chosen. For highly risk-averse investor who would have chosen the highest benchmark, the most of the return outcomes of Aktia Capital are regarded as losses. On the contrary, for more risk tolerant investor who would have chosen the lowest benchmark, the opposite is true. This feature of Omega should be kept closely in mind when interpreting the results of this study.

Figure 3 Daily return distribution of Aktia Capital

This figure presents the smoothed daily return distribution of Aktia Capital during 1999-2003. Few extreme outcomes are excluded from the picture. The vertical lines depict different loss threshold levels of -0.4%, 0.0% and 0.4% that refer to the risk aversion level of an individual investor: the higher the threshold, the higher the risk aversion level. As we move up the loss threshold level, the probability weighted loss increases and the probability weighted gain decreases. At the same time, the value of Omega decreases, which implies that the investment is more risky and less attractive.



2.3 Previous literature on mutual fund performance evaluation

This section presents the most important Finnish mutual fund studies. In addition, the key findings of Favre-Bulle and Pache (2002) on hedge fund performance are presented. The paper by Favre-Bulle and Pache (2002) is the first study that utilises the Omega framework on empirical data.

Finnish studies

Kasanen and Kinnunen (1990) is the first paper studying the performance of Finnish mutual funds. Based on the limited sample size of 11 mutual funds they find evidence on mutual fund underperformance compared to their relevant benchmark in 1988-1989. In addition, they obtain consistent performance rankings employing five different performance measures. Heikkilä (1993) finds rather analogous results for time period of 1990-1991 conducting his study with data set of 13 Finnish mutual funds. Liljeblom and Löflund (1995) report that only few funds have outperformed HEX or FOX index during 1991-1995. Further, they report that Finnish mutual fund managers do not possess market timing ability and find no evidence on performance persistence. However, on the contrary to the Liljeblom and Löflund (1995) finding, Sandvall (1999) and (2001) report significant evidence on performance persistence in equity, balanced and bond fund classes during January 1st, 1995 – June 30th, 1998. In addition, Sandvall reports abnormal returns for each fund class. Sandvall evaluates the funds with both unconditional and conditional models[23], and reports that the abnormal returns are insensitive to whether unconditional or conditional model is used. On the other hand, he points out that the abnormal returns are dependent on the time period.

In addition to these studies, there are papers that are of special interest in the context of this study. Pätäri's (2000) doctoral dissertation's first essay analyses the properties of most commonly used portfolio performance measures. He bases his paper on theoretical reasoning and on empirical findings of previously published studies. In line with several other studies, he argues that the validity of Sharpe Ratio is not consistent with an investor's actual perception of risk, since positive and negative deviations are regarded equally. His second essay makes comparative analysis between Sharpe ratio and several other risk measures both from a theoretical and an empirical point of view. All the performance ratios are analysed using each portfolio's own return distributions (i.e., total risk). Further, he performs experiments with Finnish equity data and reports that neither full-scale nor partial scale measures cannot necessarily capture total investment risk with a single risk surrogate. However, he tests different methods and concludes that downside risk measures such as target-semi-standard deviation, mean-semi-standard deviation and target-absolute-semi-deviation might be considered preferable than full-scale measures such as standard deviation and absolute deviation.

Asikainen master's thesis in 2002 studies the validity of the Sharpe ratio and the mean-variance framework in the Finnish mutual fund market. His data consist of 121 mutual funds that are marketed in Finland. Firstly, he reports that the daily returns of Finnish mutual funds are not normally distributed during 1999-2001. Secondly, he studies the impact of skewness and kurtosis on risk-adjusted performance and finds that the ranking correlations do not differ greatly whether one incorporates the third and the fourth

[23] The conditional models differ from unconditional models in that the expected returns are allowed to vary over time. Note that this study is conducted in an unconditional setting.

moments into the analysis or not. Therefore, he concludes that the Sharpe ratio is a valid measure for evaluating the risk-adjusted mutual fund performance.

Omega study

There is only one study so far that utilises the Omega measure in fund performance evaluation. Favre-Bulle and Pache (2002) examine monthly returns of 26 hedge fund strategy indexes between January 1994 and July 2002. The paper compares the hedge fund performance evaluated with the mean-variance, the mean-downside deviation, the mean-VaR and the Omega frameworks. As hedge fund returns are heavily biased, they report that the traditional mean-variance framework is an inappropriate performance measure for evaluating their risk-adjusted performance. Further, they show that the Omega, which is the only measure incorporating all the moments of the return distribution, provide more consistent results for portfolio optimisation and for performance ranking than the other measures.

3 DATA DESCRIPTION

This chapter presents the empirical data and the benchmark indexes used. Additionally, a short discussion of survivorship bias and serial correlation follows.

3.1 Data

The data in this study consist of mutual funds that are registered in Finland. The data are obtained from Investment Research Finland and reach from January 1, 1999 to December 31, 2003. As I am examining daily, weekly and monthly returns, the number of observation are 1254, 252 and 60, respectively. The data frequency used implicitly relates to the time horizon in which investors evaluate risk and return. Consequently, for example, using daily returns, one-day investment period is assumed. The returns are total returns, i.e. include reinvestment of all distributions but are net of fund expenses (for example, management fees, administrative and advertising expenses, and transaction costs). Possible front-end and back-end loads are disregarded as well. The returns are split-adjusted and due to some unrealistically huge daily price changes, the returns and the losses are limited to be at maximum +/-20%. In these cases the returns and losses are set to zero. In addition, some funds do not have price quotes for every day. In these cases their net asset values are assumed to be equal to value of the last quoted day. The returns are logarithmic and calculated from daily closing net asset values as follows:

$$r_{\ln,t} = \ln\left(\frac{V_t}{V_{t-1}}\right), \tag{28}$$

where $r_{\ln,t}$ = the logarithmic return for day t

V_t = fund net asset value at the end of day t

V_{t-1} = fund net asset value at the end of day $t-1$.

Weekly and monthly returns are calculated analogously to Equation (28). Further, to avoid the weekend-effect the weekly returns are calculated on a Wednesday-to-Wednesday basis. Monthly returns are calculated from month-end closing net asset values.

Table 1 reports the data breakdown by asset class and geographical investment orientation. Total sample size is 67 mutual funds, of which 44 are equity funds, 11 bond funds, seven asset allocation funds, and five other funds. All the equity funds are further divided into three different classes according to their investment sector: Equity Finland (N=20), Equity Europe (N=13) and Equity Global (N=11). All the seven bond funds invest in European bonds. The risk and hedge funds are classified as "Other" funds in this study. Bond money market funds are excluded in this study since according to the Mutual Fund Report of Investment Research Finland, bond money market funds cannot be evaluated by, for example, the Sharpe ratio. Appendix 1 gives the abbreviations, the full names and the asset classes of all the mutual funds in the empirical data.

Table 1 Sample breakdown

This table reports the sample breakdown according to the asset class and geographical investment orientation. The exact geographical investment orientations of risk and hedge funds are not known.

	Asset class	Geographical orientation	Number of funds
Panel A: Equity Finland	Equity	Finland	20
Panel B: Equity Europe	Equity	Europe	13
Panel C: Equity Global	Equity	Global	11
Panel D: Bond Europe	Bond	Europe	11
Panel E: Asset allocation	Asset allocation	Finland/Europe	7
Panel F: Other	Risk and hedge	?	5
Total Sample			67

The sample criteria arise form data availability and from the objectives of this study: I try to resolve whether the non-normality of fund returns complicates the risk-adjusted performance measurement. And if it does, I examine whether this phenomenon is a more severe in some particular fund markets. To answer this question, there has to be sufficient number of funds from each class to ensure the robustness of the results. Yet, for example, the number of risk and hedge funds is limited due to the young age of these fund markets in Finland.

The benchmark indexes used to calculate the excess returns are obtained from Datastream. First, HEX Portfolio is used for the funds with investment focus on Finnish equities. Second, Morgan Stanley Equity Europe Index is employed for European equity, asset allocation, risk and hedge funds. Third, Morgan Stanley Equity World Index is used for the funds with investment objectives all around the world. And finally, for the bond funds Citigroup EMU Government Bond Index 10-15 years is employed. The reason for choosing these indexes is that they cover the market under consideration most comprehensively. Furthermore, these indexes are the main benchmarks reported by funds themselves and fund reports published by independent investment researchers. Daily, weekly and monthly benchmark returns are derived from benchmarks day/week/month-end net index values analogously to Equation (28). A net index includes net dividends and coupons reinvested in the index with small adjustments made for transaction costs and other market frictions. Thus, net indexes are the suitable benchmarks for mutual fund returns that include transaction costs.

3.2 Survivorship bias and serial correlation

For example Malkiel (1995) and Elton and Gruber (1996) point out that ignoring survivorship bias might provide an overoptimistic view on the measured mutual fund performance. This results from the fact that survivorship biased sample contains only funds that have survived over the whole observation period. In addition, Elton and Gruber (1996) note that poor performance is the major reason for fund termination. A sample containing both surviving and terminated or merged funds would be free of survivorship bias. However, this study does not try to investigate the systematic under- or outperformance in the Finnish mutual fund market in general, and so, the survivorship bias is ignored.

In addition, serial correlation of the return distributions is not examined in this study and its possible impact on performance evaluation is neglected as well. However, it should be noted that the Sharpe ratio, for example, is biased upwards (downwards) in case of positive (negative) serial correlation.

4 METHODOLOGY

This chapter describes the methodology employed in this study. Some shortcomings of the methodology are discussed as well.

First of all, to examine the normality of the fund returns I employ Jarque-Bera (J-B) test statistic, which is estimated as:

$$\textit{Jarque-Bera} = \frac{n}{6}\left(skewness^2 + \frac{1}{4}(excesskurtosis - 3)^2 \right), \tag{29}$$

where $n =$ the sample size. (Jarque, Bera, 1987).

The J-B test statistic follows the chi-squared distribution with two degrees of freedom. The critical values are at 99% and 95% significance levels 9.21 and 5.99, respectively. The J-B statistic takes into account the third and fourth moments of a return distribution, but does not include the higher moments than the fourth one. Further, the major drawback of the statistics can easily be observed from Equation (29): the value of statistic increases as n increases, which implies that high frequented data get higher values than low frequented data. This, in turn, means that according to the Jarque-Bera, say, one-day observations deviate more from normality than one-year observations of that very same distribution.

The sample funds are ranked using the risk-adjusted performance measures that are calculated as expressed by their representative equations introduced in chapter 3.2. Note that the comparison of absolute values as such is not meaningful. So, one should concentrate on the rank orders only. Further, to investigate the effect of higher moments on performance evaluation and risk measurement, the differences in fund rankings are tested using a correlation test. The relevant test here is the Spearman ranking correlation test, which is developed for applications with ordinal data. Since the rankings can be positively or negatively correlated the two-tailed test is conducted. Therefore, while the null hypothesis is that there is no correlation between the ranked pairs, the counter-hypothesis is that the ranked pairs are positively or negatively correlated. The formula of the Spearman rank correlation coefficient is expressed as:

$$r = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2 - 1)}, \tag{30}$$

where n = the number of ranked pairs

d_i = the difference in rank between the two funds in question.

The Spearman ranking correlation test is also used to examine the sensitiveness of each performance measure to data frequency changes. In addition, this study also investigates separately the effect of data frequency changes on each risk proxy. The sample funds are ranked using both daily and weekly level observations. If the rank results using both data frequencies are perfectly correlated, this implies that observation interval changes do not have an effect on performance evaluation or risk measurement. The monthly level returns are omitted due to the insufficient number of observations.

The major drawback of the correlation analysis is that it does not reveal causality. Therefore, this study does not show what part of fund performance is attributed to normality and what part is attributed to non-normality. The relevant method examining causality would be regression analysis. However, it is not appealing to run regression in this study due to the very limited number of funds in some sub-samples.

To analyse the exploitation of asymmetrical investment strategies this study uses graphs. Firstly, the sample funds are ranked by their mean and skewness values. High positive mean and skewness values imply high rankings. Secondly, the sample funds are ranked by their Sharpe and Omega values. As the Sharpe ratio incorporates only the first two moments, there should not be any correlation between the rankings based Sharpe and skewness. On the contrary, Omega reacts on the higher moments as well, and therefore Omega is a sufficient measure for capturing the asymmetrical properties of a return distribution. As a consequence, if the Finnish mutual fund managers have used successfully, for example, negatively skewed investment strategies, the rankings based on skewness and Omega should be negatively correlated. In addition, I also show in some particular cases graphic illustrations of fund return distributions.

5 EMPIRICAL RESULTS

This chapter presents the empirical results. The chapter begins with providing a general outlook on the Finnish mutual performance in sub-chapter 5.1. Secondly, sub-chapter 5.2 concentrates on the return normality, and sub-chapter 5.3 on the persistence of return non-normality. The following sub-chapter 5.4 analyses the effect of non-normality on risk-adjusted fund performance. Sub-chapter 5.5 focuses on risk measurement and sub-chapter 5.6 on the exploitation of asymmetrical investment strategies. Finally, sub-chapter 5.7 studies the impact of data frequency changes on performance evaluation and risk assessment.

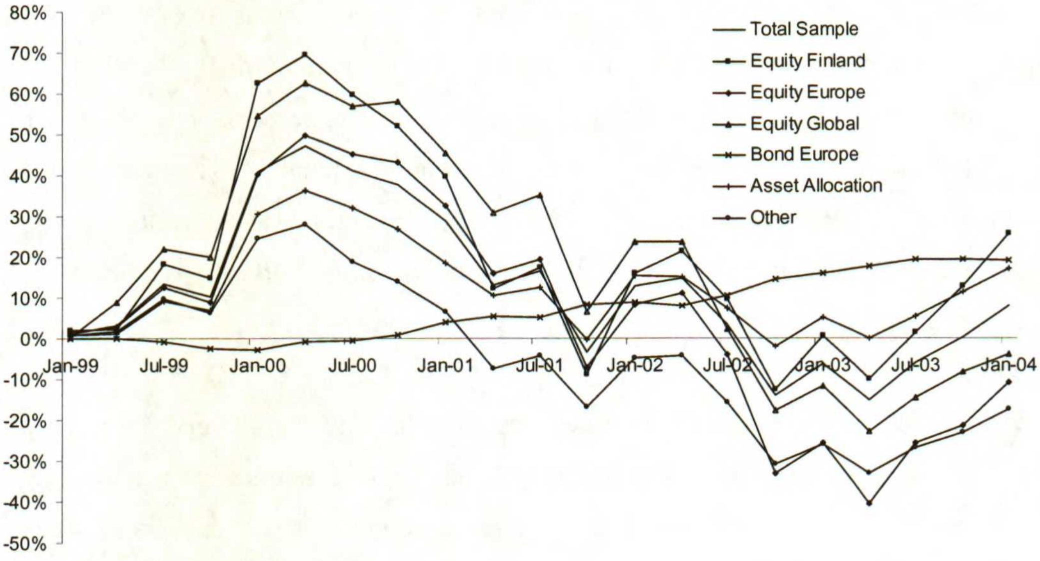
5.1 Overview of Finnish mutual fund performance

This section presents the general overview of the Finnish mutual fund performance during 1999-2003. Figure 4 shows the time- series of averaged returns for both the total sample and for each sub-sample during the observation period of 1999-2003. The observation period covers the interesting time span in the financial markets: the boom and the burst of the IT bubble, which is easily observable in Figure 4. The most drastic rise in fund values was experienced at the end of 1999, when investors' confidence on the new economy was at its highest level. At this point equity markets were booming, while returns in the bond markets remained low or negative.

Nevertheless, in March 2000 equity markets started to fall and caused very severe drop in the value of equity funds in the end of 2001. At this point investors were withdrawing their money from equities and investing it in alternative vehicles such as bonds, which can be seen in Figure 4 as the upward sloping trend in bond fund returns. In addition, the interest rate cuts have had positive effect on the performance of bond funds during 2002-2003. The economical uncertainty during the second half of the observation period has clearly affected fund performance and keeps it rather moderately positive or negative. However, funds across all the sub-samples made decent profits again in 2003.

Figure 4 Finnish mutual fund performance during 1999-2003

This figure exhibits the time-series of averaged mutual fund returns from January 5, 1999 through December 31, 2003. Total sample consist of 67 mutual funds. Sub-samples are Equity Finland (N=20), Equity Europe (N=13), Equity Global (N=11), Bond Europe (N=11), Asset Allocation (N=7) and Other (N=5). All the indexes are formed by equally weighting their constituents.



Focusing on the different fund markets separately, there are two issues that stand out distinctly. First is the outperformance of all the equity funds in the first half of the observation period. Secondly, we can observe a severe underperformance of risk and hedge funds. In general, risk and hedge funds rationale their higher administration and other fees by their skill in making abnormal returns when compared to common mutual funds. However, a quick look at the averaged return index of Finnish risk and hedge funds in Figure 4 does not offer any evidence supporting their claim that they possess superior manager skills.

Table 2 reports the general statistical properties of the Finnish mutual fund returns during the period of 1999-2003. It documents the average returns and volatilities for total sample and for each separate fund market. All the results are calculated using daily, weekly and monthly return observations. The total amount of daily, weekly and monthly observations are 1254, 252 and 60, respectively. Mean returns and volatilities provide general outlook of each market. However, the annualised returns provide better insight into the fund market developments. The annualised return of 1.61% (estimated from daily returns) for total sample is an annual average rate of return that an investor would have received if he had invested with equal weights in all the funds in the sample. It is noteworthy that the huge returns in 1999 and in the beginning of 2000 are rather suddenly vanished away during the following bearish years.

Table 2 Returns and volatilities

This table documents the average returns and volatilities that are calculated from daily, weekly and monthly net asset value observations of Finnish mutual funds from January 1, 1999 to December 31, 2003. Returns are reported as a mean and a median values. Annualised returns are calculated by multiplying the mean value by the number of observation periods in one year. I am assuming 251 one-day, 52 one-week and 12 one-month periods in a year. Volatilities are likewise reported as a mean and a median values. Annualised volatilities are calculated by multiplying the mean value by the square root of the number of observation periods in one year. Sample sizes are 1254 daily, 254 weekly and 60 monthly observations. Results are given for total sample of 67 funds and for all the six sub-samples. Sub-samples are Equity Finland (N=20), Equity Europe (N=13), Equity Global (N=11), Bond Europe (N=11), Asset Allocation (N=7) and Other (N=5).

%	Total Sample	Equity Finland	Equity Europe	Equity Global	Bond Europe	Asset Allocation	Other
Daily							
Return:							
Mean	0.0064	0.0206	-0.0086	-0.0032	0.0153	0.0138	-0.0197
Median	0.0116	0.0141	-0.0090	-0.0049	0.0153	0.0150	-0.0018
Annualised	1.6142	5.1653	-2.1521	-0.7958	3.8310	3.4555	-4.9501
Volatility:							
Mean	1.2627	1.5557	1.5373	1.4948	0.2092	0.8606	1.7468
Median	1.3890	1.5855	1.5886	1.3511	0.2247	0.9170	2.0540
Annualised	44.7329	55.1139	54.4603	52.9536	7.4122	30.4871	61.8822
Weekly							
Return:							
Mean	0.0277	0.0942	-0.0481	-0.0195	0.0767	0.0687	-0.1020
Median	0.0509	0.0586	-0.0484	-0.0260	0.0773	0.0744	-0.0192
Annualised	1.4427	4.8981	-2.5012	-1.0141	3.9874	3.5735	-5.3015
Volatility:							
Mean	2.8763	3.6257	3.3338	3.4969	0.4269	1.9599	3.9956
Median	3.0917	3.7506	3.0938	3.0455	0.4864	2.0505	4.7099
Annualised	46.3789	58.4625	53.7563	56.3852	6.8828	31.6026	64.4275
Monthly							
Return:							
Mean	0.1165	0.3956	-0.2020	-0.0819	0.3221	0.2886	-0.4282
Median	0.2136	0.2461	-0.2031	-0.1090	0.3245	0.3126	-0.0806
Annualised	1.3983	4.7474	-2.4242	-0.9829	3.8648	3.4636	-5.1384
Volatility:							
Mean	6.2020	7.9356	7.1110	7.5415	0.8685	4.2236	8.4613
Median	6.3638	8.3171	6.5928	6.3305	0.9952	4.3955	9.7497
Annualised	48.0407	61.4692	55.0812	58.4159	6.7270	32.7160	65.5409

The best performing fund class in 1999-2003 was the Finnish equities showing average annual return of 5.17%. Interestingly this class the only equity fund class that has a positive return. In addition to the Finnish equity funds, the bond funds and the asset allocation funds have been growing their asset value on average. The poor performance of the risk and hedge funds, as already illustrated in Figure 4, can be also supported by the negative average annual return of -4.95% in the "Other" column in Table 2.

Altogether it can be stated that the whole time period of 1999-2003 was quite volatile in general, as the tumultuous return indexes already illustrated in Figure 4. However, Table 2 provides a better insight into the volatility history of each fund class. Focusing on the sub-samples separately we can observe the fact that all the equity classes show higher volatilities than the bond class. Further, the asset allocation funds have been less volatile than the equity funds and more volatile than the bond funds on average. This is naturally due to the diversification effect. Not surprisingly, the risk and the hedge funds (denoted by "Other" in the tables), have been the most volatile class in the sample.

Concentrating on the equity classes only, we can observe that funds that invest in Finnish equities possess the highest volatility. In addition, data frequency seems to have an effect on the unconditional volatilities at least in some extent: the annualised volatilities expose that the European equity funds have the lowest volatility when using weekly and monthly returns, the global equity funds have the lowest volatility when using daily returns. Also, the risk and hedge funds, the asset allocation funds and all three equity fund classes exhibit lower annualised volatility value when the data frequency is higher. However, these slight dispersions are most probably due to the fact that the assumed number of observation periods in the conversion calculation does not exactly correspond to the true number of observations. Accordingly, this preliminary finding suggests that changing the frequency of return data does not have a major effect on the fund performance evaluation or risk analysis[24].

5.2 Normality of Finnish mutual fund returns

Figure 5 illustrates return histograms for the total sample and for all the sub-samples, which gives us a rough idea about the fund performance in 1999-2003. Firstly, the histograms show that returns in all fund classes seem to follow, at least approximately, the Gaussian curve. Secondly, it can be easily observed that the volatility of the total sample is lower than the volatilities of the equity funds. The histograms provide also some hints about the symmetry of the return distributions, and it seems that the distributions are a slightly positively skewed. Nevertheless, Table 3 provides more

[24] Note that the volatilities reported here are not employed in the calculation of the Sharpe ratio in the following sections since Table 1 documents the standard deviations estimated from gross returns nor the standard deviations estimated from the excess returns.

accurate information on the subject and actually gives evidence on exactly opposite view.

Figure 5 Return histograms

This figure shows daily return histograms for the total sample of 67 Finnish mutual funds and for the sub-samples. The sub-samples are Equity Finland (N=20), Equity Europe (N=13), Equity Global (N=11), Bond Europe (N=11), Asset Allocation (N=7) and Other (N=5). For demonstrative reasons only the majority of the outcomes are shown and the extreme outcomes are left out.

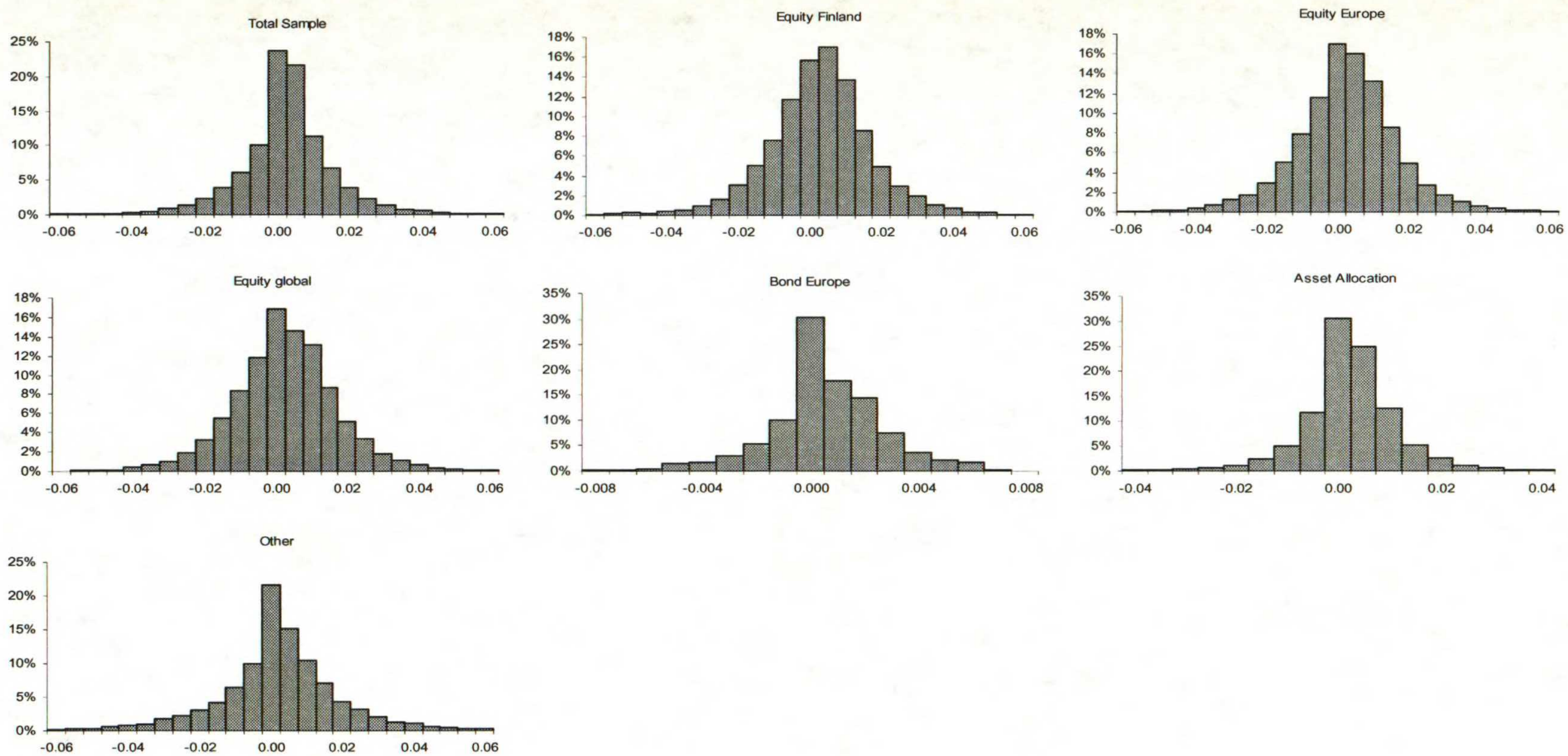


Table 3 reports skewness and excess kurtosis values and the Jarque-Bera test results. When interpreting the results one should take into account that the co-movements of the fund returns affect the distributional moments so that e.g. the skewness of averaged fund returns is different than the average of skewnesses of the individual funds. For the purposes of this study it is more convenient to calculate and report the averages and medians of individual funds. So, the statistical properties of averaged returns are ignored.

Table 3 Skewness, excess kurtosis and Jarque-Bera test results

This table reports skewness, excess kurtosis that are calculated from daily, weekly and monthly returns of Finnish mutual funds during observation period of 1999-2003. Skewness and excess kurtosis are reported as mean and median of the individual funds in each class for the whole time period. In addition, the total amount of funds is reported that have not passed the Jarque-Bera test[a] both at 0.01 and at 0.05 significance levels, and hence their return distributions are regarded as non-normal. Results are calculated for the total sample (N=67), which is further broke down into six sub-samples. Sub-samples are Equity Finland (N=20), Equity Europe (N=13), Equity Global (N=11), Bond Europe (N=11), Asset Allocation (N=7) and Other (N=5).

	Total Sample	Equity Finland	Equity Europe	Equity Global	Bond Europe	Asset Allocation	Other
Daily returns							
Skewness:							
Mean	-0.2121	-0.3127	-0.1881	-0.2588	-0.2418	0.0670	-0.0954
Median	-0.3009	-0.3355	-0.1639	-0.2399	-0.3401	-0.2737	-0.1180
Excess kurtosis:							
Mean	3.6329	3.0559	2.7102	2.8635	5.8996	5.3836	2.5947
Median	2.4023	2.6157	2.5670	2.1798	1.2535	2.3951	2.2327
Sample size	67	20	13	11	11	7	5
J-B rejected:							
1%	66	20	12	11	11	7	5
5%	66	20	12	11	11	7	5
Weekly returns							
Skewness:							
Mean	-0.1744	-0.1688	-0.1354	-0.1699	-0.4886	0.1111	-0.0172
Median	-0.1904	-0.2002	-0.0687	-0.1595	-0.5630	-0.1927	-0.1072
Excess kurtosis:							
Mean	1.6566	1.4257	2.4174	1.1067	0.9732	2.6291	1.9531
Median	1.3785	1.2696	1.8515	1.1752	1.0638	1.9233	1.5571
Sample size	67	20	13	11	11	7	5
J-B rejected:							
1%	62	18	10	11	11	7	5
5%	62	18	10	11	11	7	5
Monthly returns							
Skewness:							
Mean	-0.0924	0.1264	-0.5299	-0.2122	-0.3236	0.5220	0.0825
Median	-0.1481	0.1230	-0.6675	-0.2920	-0.3147	0.1284	-0.1865
Excess kurtosis:							
Mean	0.7389	0.9394	0.8988	-0.0103	-0.1240	2.0708	1.2029
Median	0.5674	0.8145	0.8704	-0.0514	-0.1143	1.4977	0.8300
Sample size	67	20	13	11	11	7	5
J-B rejected:							
1%	56	14	12	11	11	3	5
5%	61	16	12	11	11	6	5

[a] J-B statistic follows chi-squared distribution with two degrees of freedom. The critical values are 9.21 (1%) and 5.99 (5%).

Skewness

Focusing first on the results calculated from the daily returns we can observe from Table 3 that the third distributional moment, skewness, has been negative for the total sample and throughout the sub-samples[25] except for the asset allocation funds. The positive mean skewness value for asset allocation funds results mainly from the high number of extreme positive returns for Mandatum Neutral. Actually, there are few other funds, which exhibit a lot of either extreme negative or extreme positive outcomes, and therefore, they report very low or high mean skewness value. For this reason the median values of skewness may give us a better insight into the symmetrical properties of fund returns than means. The median skewness values show that the bond funds and the equity funds investing in Finland have been the most negatively skewed classes, whereas the risk and the hedge funds, a bit surprisingly, exhibit the least negatively skewnesses. However, there is a huge dispersion between the skewnesses of the five risk and hedge funds[26]. While three funds out of five, Mandatum Vipu, Gyllenberg Momentum and Conventum Focus, have negative skewnesses from -11 to -35, the remaining two funds, Mandatum Kontra and Seligson & Co Phalanx, show positive skewnesses of 25 and 10, respectively. Further, we can presume that the highly asymmetrical nature of risk and hedge fund returns may affect their performance measurement as well. This issue is further examined in the following sub-chapter.

Changing the data frequency reveals an interesting feature in the skewness values of the funds. Concentrating on the total sample it seems that at the wider observation intervals, the returns are less negatively skewed. However, the relationship is not that clear when we examine the sub-samples separately. For example, the negative skewness values (both mean and median) for equity funds investing in Finland decrease as we move from daily returns to weekly returns. And finally, when examining monthly returns, the skewness values are surprisingly highly positive. In fact, only one fund (Nordea Fennia Plus) out of 20 Finnish equity funds exhibits positive skewness value when the statistics are calculated using daily return, whereas for monthly returns the total number of Finnish equity funds with positive values is 14. Due to these mixed results, we cannot

[25] Recall the Scott and Hovath (1980) argument introduced in section 2.1.2 that investors desire high odd moments (mean, skewness, etc.) and low even moments (standard deviation, kurtosis, etc.).

[26] For brevity, the skewness values for individual funds are not shown in the Table 3.

make any generalisations on how the observation interval changes affect the symmetrical properties of Finnish mutual funds.

Excess kurtosis

The fourth moment, kurtosis, which is presented here as excess kurtosis, measures the peakedness and "tail-heaviness" of the return distributions. From Table 3 we can notice that the daily return means of excess kurtosis are all positive and greater than median values throughout the sub-samples. Accordingly, the distribution of the kurtosis values is positively skewed. For this reason, we should focus on the median values since they are more informative for us. The medians exhibit that funds investing in Finnish equities and European equities are the most peaked and heavy-tailed classes. The heavy-tails of the return distribution in turn imply that the Finnish equity and European equity funds have experienced more extreme outcomes than the rest of the funds. In addition, the overall results for excess kurtosis values estimated from weekly returns are in line with that of estimated from daily returns. The highest excess kurtosis is reported for asset allocation funds, but this is mainly due to the inaccurate return data for Mandatum Neutral.

Next, we examine the effect of data frequency changes on excess kurtosis. Table 3 shows that excess kurtosis decreases as the observation interval increases from daily observations to monthly observations. The finding is in parallel with earlier studies concerning individual assets by Vaihekoski (1997) and Aparicio and Estrada (2001). In addition, the Asikainen (2002) paper on Finnish funds reports that returns show decreasing non-normality when the observation interval increases. Nevertheless, the finding that excess kurtosis values for weekly returns are smaller than excess kurtosis values for daily returns is line with the previous literature.

Jarque-Bera test

Table 3 also reports the total number of funds which are non-normally distributed according to the Jarque-Bera (J-B) test at 1% and 5% significance levels. When the J-B statistic is estimated from the daily returns, only one fund (Gyllenberg EU Equities) passes the J-B test, and therefore, it can be considered normally distributed. Changing the data frequency of the returns, we can observe that the number of non-normally distributed funds decreases as the observation interval widens. When the returns are estimated from the weekly observations, the normality assumption for 62 funds is rejected at 1% level. Correspondingly, when the interval is widened to monthly observations, the normality assumption is rejected at 1% level for 56 funds of the total of 67 funds. However, it is evident that monthly returns show decreasing non-normality when compared to, for example, daily returns since the Jarque-Bera statistic is sensitive to the amount of observations. It can directly be observed from Equation (29) that the statistic value increases as the number of observations increases, and therefore it exhibits increasing non-normality for high frequented data. In addition, it is very important to be aware that Jarque-Bera statistic measures only the impact of skewness and kurtosis, the third and the fourth moments, and ignores all the moments of higher order. This notice is essential when interpreting the results in the following sections.

5.3 Persistence of non-normality

In addition to the examination of the fund return normality during the five-year time period of 1999-2003, this study explores the fund payout profiles in each year separately. If the payout profiles have been non-normal for several subsequent years and the non-normality has thus been a persistent phenomenon, it is interesting to try to find reasons for that. Table 4 reports the medians of the skewness and excess kurtosis values for each one-year observation period during 1999-2003. Due to the limited amount of observations within one-year time period, the Jarque-Bera test is conducted only using daily returns.

Table 4 Persistence of non-normality

This table reports the median skewness and excess kurtosis values for Finnish mutual fund returns in each separate year from 1999 to 2003. Results are calculated from daily returns. The total amount of funds is reported that have not passed the Jarque-Bera test[a] at 1% significance level, and hence their return distributions are regarded as non-normal. Results are calculated for the total sample (N=67) and for all the sub-samples: Equity Finland (N=20), Equity Europe (N=13), Equity Global (N=11), Bond Europe (N=11), Asset Allocation (N=7) and Other (N=5).

	Total Sample	Equity Finland	Equity Europe	Equity Global	Bond Europe	Asset Allocation	Other
1999							
Skewness	-0.3025	-0.1644	-1.5288	-0.1614	0.2001	0.3878	-0.0494
Excess kurtosis	2.4895	2.7787	2.8408	1.1278	1.0557	3.4564	4.2349
Sample size	67	20	13	11	11	7	5
J-B rejected (1%)	56	17	10	10	11	3	5
2000							
Skewness	-0.2719	-0.2445	-0.3370	-0.2405	-0.2687	-0.3746	-0.3610
Excess kurtosis	1.2786	1.3448	1.0477	1.4723	0.6143	1.2536	1.5149
Sample size	67	20	13	11	11	7	5
J-B rejected (1%)	62	19	11	10	11	7	4
2001							
Skewness	-0.2876	-0.2694	-0.2930	-0.7967	-0.5412	-0.1687	0.0405
Excess kurtosis	1.5284	1.0189	1.8645	4.8177	1.8453	0.8131	1.0281
Sample size	67	20	13	11	11	7	5
J-B rejected (1%)	63	20	11	10	10	7	5
2002							
Skewness	-0.0631	-0.2162	-0.0052	0.0673	-0.0631	-0.0707	-0.2033
Excess kurtosis	0.9600	1.1950	1.2498	0.5764	-0.1150	0.7384	0.9600
Sample size	67	20	13	11	11	7	5
J-B rejected (1%)	60	16	11	10	11	7	5
2003							
Skewness	0.2286	0.3284	0.5430	0.2600	-0.7454	0.2636	0.1572
Excess kurtosis	1.2602	1.1873	2.5060	1.3715	1.1805	1.0830	1.9399
Sample size	67	20	13	11	11	7	5
J-B rejected (1%)	66	20	13	11	11	7	4

[a] J-B statistic follows chi-squared distribution with two degrees of freedom. The critical values are 9.21 (1%) and 5.99 (5%).

Skewness

First, focusing on the skewness values that are based on the total sample, we can observe that during the first four years (1999-2002) the funds exhibit negative skewed returns. In 1999, during the IT boom and sharp rise in equity markets, the funds exhibit highest negatively skewed returns, whereas in 2003 skewness has turned to positive. Further, the symmetrical properties of the Finnish, European and global equity fund returns are in line with that of total sample: negative skewness values in the beginning and positive values in the end of the total period. Whereas the total sample shows the highest negative skewness value in 1999, the Finnish and global equity funds show the most negative skewness values in 2001. In 2001 the IT bubble burst and the equity markets fell drastically and caused huge losses for investors with long positions in equities.

The year 1999 exhibits the most negative skewness values for total sample in the total observation period of 1999-2003. This is due to the payout profiles of the equity funds, which show systemically negatively skewed returns in that particular year. Therefore, it is possible that the equity fund managers have exploited asymmetrical investment strategies to earn those huge profits.

As illustrated earlier in Figure 4, the Finnish funds investing in European bonds have performed relatively poorly in the first part of the whole observation period before turning into profit in the end of summer 2000. However, contrary to the equity funds, the bond funds show positive skewness in 1999 and negative skewness in each year in the period of 2000-2003. And similar to the European equity funds, the return distributions of the bond funds exhibit most negative values while they have been the most profitable, which is year 2003 in this case. This finding again may indicate that fund managers have exploited asymmetrical investment strategies.

The return distributions of asset allocation, risk and hedge funds do not show persistent negative or positive values skewness during 1999-2003. In fact, asset allocation funds show positive skewness in the buoyant 1999 and 2003 and negative skewness in the bearish 2000, 2001 and 2002. The shape of the risk and hedge fund payout profiles have been fluctuating rather randomly during the time period of 1999-2003: negative skewness values in 1999, 2000 and 2002 positive values in 2001 and 2003. Yet, they have one common feature; i.e. they show the most negative skewness in 2000.

Excess kurtosis

The fourth moment, excess kurtosis, exhibits that in the bullish 1999 the returns have been more peaked and the funds have experienced more extreme outcomes than during the following years. This phenomenon can be observed throughout the sub-samples, although the asset allocation and the risk and hedge funds have the most fat-tailed distributions in the total sample. The high value of excess kurtosis for the asset allocation funds is rather surprising since one could imagine that a fund formed by balancing equities and bonds would have fever extreme outcomes. However, as argued by Osband (2002) assets with low tail risk can still cause a very fat-tailed portfolio, which seems to be the case here. Although the excess kurtosis has been moderate during 2000-2003, the evidence regarding 1999 supports the view that we should also be concerned about the moments of higher order than mean and variance.

Jarque-Bera test

According to the Jarque-Bera test, 56 funds out of total of 67 are regarded as non-normal at 1% level, and therefore the remaining 11 are considered normally distributed in 1999. In the following years the normality assumption is rejected even more often. This may sound odd, since the year 1999 reports the most negative skewness and the most positive excess kurtosis values than the rest of the observation periods. However, this result is due to the large deviation of Jarque-Bera statistic values in 1999: while some of the funds exhibit moderate values and hence are considered normally distributed, the majority exhibit large values resulting large median values of skewness and excess kurtosis in Table 4. Nevertheless, the majority of the sample funds are not normally distributed when they are examined in each year separately.

Overall, it can be concluded that when the bond funds are excluded, the historical return distributions of Finnish mutual funds exhibit negative skewness during 1999-2002 and positive excess kurtosis during the whole observation period of 1999-2003. The bond funds show positive skewness in 1999, negative skewness in 2000-2003 and positive excess kurtosis during 1999-2003. As a consequence, at least the daily returns distributions cannot be regarded as normally distributed, which is in line with the Asikainen (2002) finding. All in all, as the non-normality of Finnish mutual fund returns has been persistent phenomenon during 1999-2003, it is interesting to explore how the finding affect performance evaluation and risk measurement. Sub-chapters 5.4 and 5.5 are dedicated to these issues. In addition, sub-chapter 5.6 tries to find evidence for the question whether the Finnish mutual fund managers have exploited deliberately asymmetrical investment strategies.

5.4 Mutual fund performance ranking

This sub-chapter analyses the effect of return non-normality on risk-adjusted performance. Firstly, the sample funds are ranked according to each performance measure presented in sub-chapter 2.2. Secondly, the consistency of the rankings based on the performance evaluation methods is examined by conducting the Spearman correlation test. The performance measure values and their corresponding rankings are reported in Appendices 2-4. The analysis is conducted using daily and weekly returns, but for brevity the results are reported on a daily level only. Sub-chapter 5.7 focuses on the ranking differences between daily and weekly level observations. Monthly returns are excluded, since especially the VaR- and Omega figures would lack validity due to the limited number of observations (60). For example Favre-Bulle and Pache (2002) report that the sufficient amount of observations for Omega is around 100-200

Finnish equity funds

Table 5 reports the Spearman ranking correlation coefficients for all three equity fund classes. Correlations are based on the performance rankings which are calculated from the daily return distributions. Panel A in Table 5 documents the results for the funds that invest in Finnish equities. Panel A documents a very high (0.9 or higher) correlation coefficients for all the measures, except for the Omega. Actually there are a number of perfect correlations showing a coefficient of one. However, concentrating first on the Sharpe ratio, it can be noted that it shows statistically significant correlations (correlations of 0.9 or 0.91) with all its adjusted forms, but not with Omega. The finding suggests that the risk-adjusted performance of funds investing in Finnish equities may be affected by higher distributional moments than the first two ones. As we recall from section 2.2.3 that the VaR Sharpe embodies only mean and variance, just like the original Sharpe ratio, it could be confusing why there is some dispersion between these two. The reason underlies on the way their investment risk is defined and calculated: the standard deviation of the Sharpe is calculated from the excess return distribution over the benchmark index, whereas the VaR figures are calculated from the gross return distribution. This fact should be kept closely in mind when the results are interpreted throughout this study.

Further, the CFVaR and the R/SV rankings correlate almost perfectly with each other, but not with the Sharpe or the VaR rankings. This implies that taking also the third moment, skewness, into account gives us a little bit more information from the distributional characteristics of the funds investing in Finnish equities. At the same time, addition of the fourth moment, excess kurtosis, does not give any extra contribution into our analysis. Although the Finnish equity funds show the highest excess kurtosis values among the sub-samples as reported in section 5.1, the fat-tails of the return distributions do not seem to have an effect on their rankings. Also, the R/SV method does not seem to be sensitive to the target return selected. This actually holds also for all the other fund classes. The finding implies that the level of investor's risk aversion does not have an effect on the risk-adjusted performance evaluation in the mean-semi-variance framework.

The traditional performance measures are extremely unanimous in evaluating risk-adjusted performance of the funds investing in Finnish equities. On the contrary, the Omega measure is not in line with the others, which may indicate the presence of higher distributional moments than kurtosis. Omega at target return of -0.2% has the highest correlation with the traditional measures. Loss threshold level of -0.2 % refers to a rather high risk tolerance level. Note that risk threshold level of -0.2%, implies that an investor considers all the daily returns below -0.2% as a loss, and all the daily returns above -0.2% as a gain. It may sound strange that return outcomes from -0.2% to 0% are considered a gain, although negative returns are not regarded as gain *per se*. However, a negative loss threshold level could be a natural choice since often fund performance is compared against, for example, a stock index which is also negative in a bearish market conditions. And if a fund outperforms its benchmark index, it is often considered as a good investment.

Table 5 Performance ranking correlations: Finnish equity, European equity, global equity funds

This table gives the Spearman correlation coefficients between the performance rankings based on different performance evaluation frameworks. Correlations are calculated for Finnish mutual funds investing in Finnish equities (Panel A), European equities (Panel B) and global equities (Panel C). VaR Sharpe and CFVaR Sharpe are estimated at 1% and 5% confidence levels. Reward-to-semi-variance (R/SV) is estimated using three different exogenously determined target returns of -0.2%, 0.0% and 0.2%. The returns lower than the target return levels are regarded as "bad" volatility, and therefore they are considered the downside risk of an investment. Omega is estimated using three exogenously determined loss threshold levels of -0.2%, 0.0% and 0.2%. The returns lower (higher) than the loss threshold levels are regarded as a loss (a gain).

		VaR Sharpe		CFVaR Sharpe		R/SV			Omega		
	Sharpe	1%	5%	1%	5%	-0.2 %	0.0 %	0.2 %	-0.2 %	0.0 %	0.2 %
Panel A: Equity Finland											
Sharpe	1***										
VaR Sharpe (1%)	0.90***	1***									
VaR Sharpe (5%)	0.90***	1***	1***								
CFVaR Sharpe (1%)	0.91***	0.99***	0.99***	1***							
CFVaR Sharpe (5%)	0.90***	1***	1***	0.98***	1***						
R/SV (-0.2%)	0.90**'	1***	1***	0.99***	1***	1***					
R/SV (0.0%)	0.90***	1***	1***	0.99***	1***	1***	1***				
R/SV (0.2%)	0.90**	1***	1***	0.99***	1***	1***	1***	1***			
Omega (-0.2%)	0.69***	0.68***	0.68***	0.66***	0.70***	0.69***	0.69***	0.69***	1***		
Omega (0.0%)	0.13	0.19	0.19	0.16	0.20	0.19	0.19	0.19	0.18	1***	
Omega (0.2%)	-0.14	-0.12	-0.12	-0.13	-0.15	-0.13	-0.13	-0.13	-0.49	0.24	1***
Panel B: Equity Europe											
Sharpe	1***										
VaR Sharpe (1%)	0.98***	1***									
VaR Sharpe (5%)	0.98***	1***	1***								
CFVaR Sharpe (1%)	0.98***	0.99***	0.99***	1***							
CFVaR Sharpe (5%)	0.98***	1***	1***	0.99***	1***						
R/SV (-0.2%)	0.98***	1***	1***	0.99***	1***	1***					
R/SV (0.0%)	0.98***	1***	1***	0.99***	1***	1***	1***				
R/SV (0.2%)	0.98***	1***	1***	0.99***	1***	1***	1***	1***			
Omega (-0.2%)	0.66**	0.70**	0.70**	0.68**	0.70**	0.70**	0.70**	0.70**	1***		
Omega (0.0%)	0.64**	0.60**	0.60**	0.65**	0.60**	0.60**	0.60**	0.60**	0.46	1***	
Omega (0.2%)	-0.18	-0.21	-0.21	-0.19	-0.21	-0.21	-0.21	-0.21	-0.43	0.26	1***
Panel C: Equity Global											
Sharpe	1***										
VaR Sharpe (1%)	1***	1***									
VaR Sharpe (5%)	1***	1***	1***								
CFVaR Sharpe (1%)	1***	1***	1***	1***							
CFVaR Sharpe (5%)	1***	1***	1***	1***	1***						
R/SV (-0.2%)	1***	1***	1***	1***	1***	1***					
R/SV (0.0%)	1***	1***	1***	1***	1***	1***	1***				
R/SV (0.2%)	1***	1***	1***	1***	1***	1***	1***	1***			
Omega (-0.2%)	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	1***		
Omega (0.0%)	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.53	1***	
Omega (0.2%)	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	-0.70	0.49	1***

*** significant at 1% level, ** significant at 5% level

In addition, it is noteworthy that Omega with a positive loss threshold level of 0.2% exhibits negative ranking correlations towards all the measures except Omega (0%). This indicates that a highly risk averse investor would rank the funds investing in Finnish equities radically differently if he also took the information contained in the higher moments than kurtosis into account.

Overall, Omega (-0.2%) shows strong statistical correlation with the traditional measures. This result suggests that the two first distributional moments alone are fairly sufficient for capturing the risk and reward properties of the funds investing in Finnish equities.

European equity funds

Panel B in Table 5 provides the results for the funds investing in European equities. In line with the results for the Finnish equity funds in Panel A, the European funds are ranked very similarly by the Sharpe ratio and by all the other traditional measures. Actually, although Jarque-Bera test classified 12 out of 13 funds as non-normal, they correlate almost perfectly with each other even if skewness (R/SV) and excess kurtosis (CFVaR Sharpe) are taken into account. In addition, the Omega at two different target returns of -0.2% and 0.0% exhibits statistically significant correlation with the traditional measures. The result suggests that the payout profiles of the funds investing in European equities can be well evaluated by simply using the Sharpe ratio alone.

Global equity funds

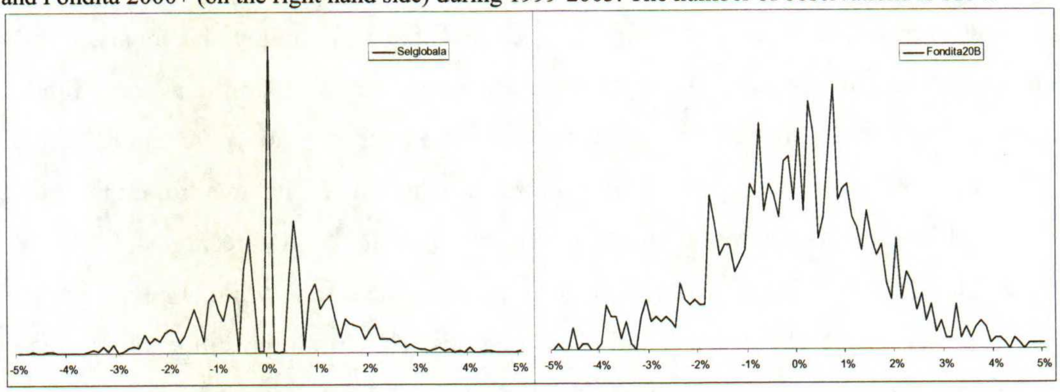
Furthermore, Panel C in Table 5 reports the results for the funds with global investment focus. Interestingly, the Sharpe ratio, the R/SV, the VaR Sharpe and the CFVaR Sharpe give equal rankings for all the 11 global equity funds. This is surprising result since according to the Jarque-Bera test all the sub-sample funds have non-normally distributed returns. However, as already reported in Table 3 the returns of global equity funds are less negatively skewed and posses less excess kurtosis than the average fund in the total sample. Interestingly, the Omega measures do not give statistically significant correlations with the other measures, which may be due to either the presence of higher distributional moments or incorrect the loss thresholds. Further, Omega (0.0%) shows negative correlation with the other measures, while Omega (-0.2%) and Omega (0.2%) show positive correlations. This mixing result suggests that some of the global equity funds have very ill-natured return distributions and the deviations from normality are due to higher distributional moments than kurtosis.

From Panel C in Appedix 3 we can observe interesting variations in the rankings of Seligson Global Top 25 Brands and Fondita 2000+. Moreover, Seligson Global Top 25 Brands and Fondita 2000+ show moderate negative skewness values of -0.02 and -0.39 and excess kurtosis values of 1.09 and 2.01, respectively. So, according to the measures which take into account only the first four moments, these moderate devitations from normality does not affect their performance ranking at all: Panel C in Appendix 3 shows that the traditional measures rank Seligson Global Top 25 Brands at third place in the sub-sample size of 11 funds. On the other hand, at a loss threshold levels of (-0.2%), (0.0%) and (0.2%) Omega ranks Seligson Global Top 25 Brands at 5th, 11th and 6th place. Note that the rankings alter rather randomly when the risk tolerance level is changed.

Further, Figure 6 shows the reason for this variability in rankings, in which the peculiar return distributions of Seligson Global Top 25 Brands and Fondita 2000+ are illustrated. Firstly, the symmetry of Seligson's return distribution is astonishing. Secondly, as mentioned, Seligson's distribution has no fat-tails either. As a consequence, the traditional measures give unanimously consistent rankings. However, Omega reacts to the exceptional shape of the return distribution, which is due to the higher distributional moments than the fourth one. Further, the attractiveness of the funds is highly dependent on investor's attitude towards investment risk.

Figure 6 Daily return distributions of Seligson Global Top 25 Brands and Fondita 2000+ during 1999-2003

This figure shows the daily return distributions of Seligson Global Top 25 Brands (on the left hand side) and Fondita 2000+ (on the right hand side) during 1999-2003. The number of observations is 1254.



In addition, all the traditional measures rank Fondita 2000+ systematically at fourth place and Omegas rank it at 10th, 1st and 4th place. Figure 6 also illustrates the daily return distributions for the fund. Despite the fact that the fund does not exhibit neither high skewness nor high excess kurtosis values, we can observe that the shape of the distribution is very ill-natured and far from being normal. Accordingly, the R/SV and the CFVaR Sharpe do not make a difference to rankings already obtained by the traditional Sharpe. Omega is the only measure which can identify this kind of non-normality in return distributions.

However, the results based on the Omega framework should be interpreted cautiously. The rankings seem to be very sensitive to the loss threshold level employed, which can be observed from Table 5. In many cases correlations may change from statistically significant positive correlation to strong negative correlation.

European bond funds

Table 6 reports the correlations between all the performance measures for European bond (N=11), Asset allocation (N=7) and other funds (N=5). The "Other" fund class consists of risk and hedge funds. First, it should be noted that the excess returns for all the bond funds in Panel D are negative, since none of them beats the Citigroup Government Bond Index in the period of 1999-2003. As a result, the results obtained by Sharpe and its adjusted forms do not really have any interpretation. This is due to the reversal rank order critic by Jobson and Korkie (1981) presented earlier in section 2.2.1.: if two randomly selected funds have equal negative excess returns, the one with a higher standard deviation has a less negative Sharpe value and is therefore viewed superior to the other although the common sense would suggest the opposite.

However, as Omega is straightforwardly calculated from the return distributions, it does not suffer from same kind of problems. Omega (-0.2%) exhibits negative and Omega (0%) moderate negative and positive correlations towards the traditional performance measures, whereas Omega (0.2%) presents rather high positive correlations. In addition, Omegas (-0.2%) and (0.2%) are almost perfectly negatively (-0.98) correlated with each other. This results from the small daily changes in the bond fund net asset values. As reported in Table 1, the mean of the standard deviations, which are estimated from the bond funds' daily returns, is only 0.000021%. Accordingly, the loss threshold level changes from -0.2% to 0.0% and from 0.0% to 0.2% could be too wide. Actually, the average probability mass below -0.2% of all the bond funds is around 14%, whereas the average probability mass below 0.2% is around 85%. Thus, it is evident that the Omega values, and rankings as well, change drastically when the loss threshold level is changed so significantly.

Nevertheless, due to the problems caused by negative excess values the results for European bond funds are very unconvincing. Therefore, it is difficult to draw any generalisations about the effect of higher moments on the risk-adjusted performance of bond funds. The evidence, however, suggests that when the excess returns are negative the best functioning method seems to be the Omega framework, although it is very sensitive to the loss threshold level selected.

Table 6 Performance ranking correlations: European bond, Asset allocation, risk and hedge funds

This table gives the Spearman correlation coefficients between the performance rankings based on different performance evaluation frameworks. Correlations are calculated for Finnish mutual funds investing in European bonds (Panel D). In addition, correlations are calculated for Finnish asset allocation (Panel E) and risk and hedge funds (Panel F). VaR Sharpe and CFVaR Sharpe are estimated at 1% and 5% confidence levels. Reward-to-semi-variance (R/SV) is estimated using three different exogenously determined target returns of -0.2%, 0.0% and 0.2%. The returns lower than the target return levels are regarded as "bad" volatility, and therefore they are considered the downside risk of an investment. Omega is estimated using three exogenously determined loss threshold levels of -0.2%, 0.0% and 0.2%. The returns lower (higher) than the loss threshold levels are regarded as a loss (a gain).

		VaR Sharpe		CFVaR Sharpe		R/SV			Omega		
	Sharpe	1%	5%	1%	5%	-0.2 %	0.0 %	0.2 %	-0.2 %	0.0 %	0.2 %
Panel D: Bond Europe											
Sharpe	1***										
VaR Sharpe (1%)	0.66**	1***									
VaR Sharpe (5%)	0.66**	1***	1***								
CFVaR Sharpe (1%)	0.56	0.89***	0.89***	1***							
CFVaR Sharpe (5%)	0.48	0.80***	0.80***	0.47	1***						
R/SV (-0.2%)	0.58	0.99***	0.99***	0.88***	0.81***	1***					
R/SV (0.0%)	0.58	0.99***	0.99***	0.88***	0.81***	1***	1***				
R/SV (0.2%)	0.61	0.96***	0.96***	0.82***	0.83***	0.95***	0.95***	1***			
Omega (-0.2%)	-0.40	-0.80***	-0.80***	-0.57	-0.87***	-0.81***	-0.81***	-0.77**	1***		
Omega (0.0%)	-0.39	-0.02	-0.02	-0.07	0.11	0.00	0.00	-0.06	-0.50	1***	
Omega (0.2%)	0.40	0.79***	0.79***	0.56	0.87***	0.80***	0.80***	0.75**	-0.98***	0.35	1***
Panel E: Asset Allocation											
Sharpe	1***										
VaR Sharpe (1%)	0.75	1***									
VaR Sharpe (5%)	0.75	1***	1***								
CFVaR Sharpe (1%)	0.86**	0.96***	0.96***	1***							
CFVaR Sharpe (5%)	0.75	1***	1***	0.96***	1***						
R/SV (-0.2%)	0.86**	0.96***	0.96***	1***	0.96***	1***					
R/SV (0.0%)	0.86**	0.96***	0.96***	1***	0.96***	1***	1***				
R/SV (0.2%)	0.86**	0.96***	0.96***	1***	0.96***	1***	1***	1***			
Omega (-0.2%)	0.50	0.86**	0.86**	0.71	0.86**	0.71	0.71	0.71	1***		
Omega (0.0%)	-0.07	-0.32	-0.32	-0.39	-0.32	-0.39	-0.39	-0.39	-0.11	1***	
Omega (0.2%)	-0.46	-0.82	-0.82	-0.68	-0.82**	-0.68	-0.68	-0.68	-0.96***	0.04	1***
Panel F: Other											
Sharpe	1***										
VaR Sharpe (1%)	0.90	1***									
VaR Sharpe (5%)	0.90	1***	1***								
CFVaR Sharpe (1%)	0.90	1***	1***	1***							
CFVaR Sharpe (5%)	0.90	1***	1***	1***	1***						
R/SV (-0.2%)	0.90	1***	1***	1***	1***	1***					
R/SV (0.0%)	0.90	1***	1***	1***	1***	1***	1***				
R/SV (0.2%)	0.90	1***	1***	1***	1***	1***	1***	1***			
Omega (-0.2%)	0.45	0.25	0.25	0.25	0.25	0.25	0.25	0.25	1***		
Omega (0.0%)	-0.50	-0.70	-0.70	-0.70	-0.70	-0.70	-0.70	-0.70	-0.65	1***	
Omega (0.2%)	-0.50	-0.70	-0.70	-0.70	-0.70	-0.70	-0.70	-0.70	-0.65	1***	1***

*** significant at 1% level, ** significant at 5% level

Asset allocation funds

Concentrating on the Panel E in Table 6, which gives the correlations for the asset allocation funds, we find again that the traditional performance measures tend to give fairly similar rankings. Note that the correlation coefficients fall pretty drastically no matter how small the deviations between rankings are, since the sample size is only seven funds. Nevertheless, it is noteworthy that the VaR Sharpe at both 5% and 1% levels and the CFVaR Sharpe at 5% level do not have statistically significant correlations with the Sharpe ratio. Still, the R/SV has a high correlation with the Sharpe ratio. This is a confusing result and we cannot make straightforward interpretations about the presence or the effect of moments from two to four. Therefore, the most feasible reason for the mixed results is that the deviations in rankings arise from the methodological reasons: standard deviation of the Sharpe ratio is estimated from the excess returns, while the other risk proxies are estimated from the gross returns.

Furthermore, Omega (-0.2%) and Omega (0%) give invariably negative values towards the Sharpe and its adjusted forms. Yet, the rankings based on the traditional performance measures and the Omega assuming a high risk tolerance level of -0.2% show strong correlation with each other. Therefore, this evidence suggests that there is no or weak impact of higher distributional moments on the risk-adjusted performance of Finnish asset allocation funds. Further, the risk-adjusted performance of Finnish asset allocation funds can be well assessed by the traditional Sharpe ratio.

Risk and hedge funds

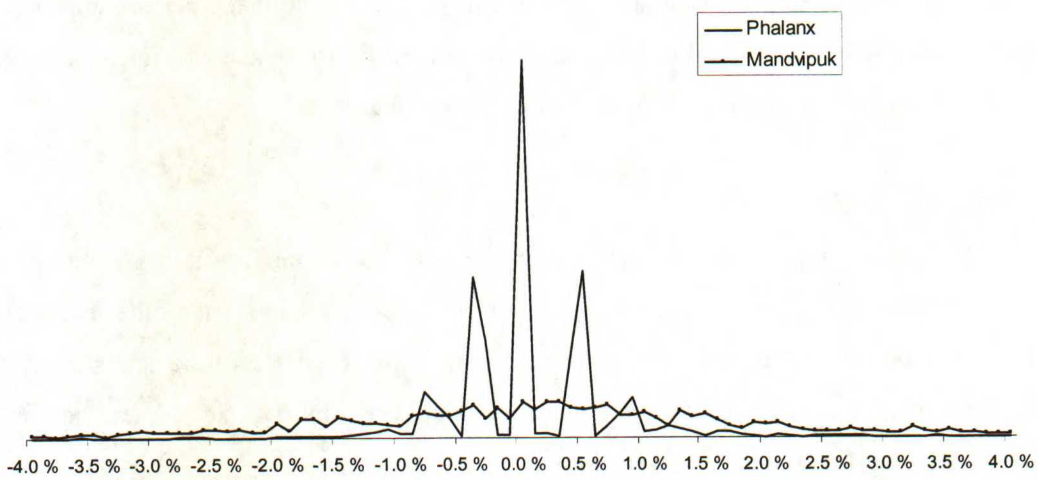
Panel F in Table 6 reports the ranking correlations between the five risk and hedge funds. The traditional performance measures correlate perfectly with each other expect with the Sharpe ratio at a level of 0.9. Yet, a correlation of 0.9 is not a statistically significant correlation. The performance measure values and rankings for risk and hedge funds are reported in Panel F in Appendix 4.

Further, in accordance with the results for the global equity funds, the rankings for the risk and hedge funds obtained from the Omega framework do not correlate with the traditional measures. It must be emphasised that, for example, Omega (-0.2%) has the weakest, and far from being statistically significant, correlation with the traditional measures in the risk and hedge fund class. The evidence supports the argument that the measures incorporating only the first four moments may not be sufficient for evaluating the risk-adjusted performance of risk and hedge funds.

The rankings also differ within the Omega framework. This is mainly due to the cranky payout profile of a hedge fund called Seligson Phalanx. Whereas Omega (-0.2%) and the traditional measures rank it at the first place, Omega (0%) and Omega (0.2%) rank it at the fifth, i.e. the last, place. Figure 7 illustrates the daily return distribution of Seligson Phalanx. For comparison purposes the daily return distribution of Mandatum Vipu is also presented. Firstly, the return distribution of Seligson Phalanx has five eye-catching peaks. Secondly, the distribution is symmetrical around its mean exhibiting a very small positive skewness value of 0.01. Thirdly, the distribution has no disturbingly fat-tails either as it shows excess kurtosis value of 3.74. Further, it has the highest mean return in the sub-sample, and therefore every measure except Omega (0%) and Omega (0.2%) rank it at the first place.

Figure 7 Daily return distributions of Seligson Phalanx and Mandatum Vipu in 1999-2003.

This figure shows the daily return distributions of Seligson Phalanx and Mandatum Vipu in 1999-2003. The number of observations is 1254. Few extreme outcomes of Mandatum Vipu are excluded from the picture.



Then again we come to the important issue of what return level is satisfactory for the investors. The attractiveness of Seligson Phalanx depends highly on investors' individual stance towards investment risk. At a high risk tolerance level of -0.2%, around 34% of the return outcomes are viewed as a loss. The remaining 64% are viewed as a gain. On the other hand, instead of accepting any negative outcomes, we can set our loss to zero. In that case, the highest peak in the return distribution is considered a loss, and therefore 66% percent of the probability mass lies under the loss threshold and only the remaining 34% is considered as a gain. As a result, the Omega value falls drastically and the ranking of Seligson Phalanx changes from the first position to the last position. Correspondingly, for a very risk-averse investor exhibiting a loss threshold level of 0.2%, the majority of return outcomes is regarded as loss, and therefore Omega (0.2%) regards the fund as the top value destroyer in the risk and hedge fund class.

Accordingly, although the return distribution of Phalanx Seligson does not suffer from asymmetrical or fat-tailed problems, it is still very far from being normally distributed. However, the non-normality is due to the higher moments than the fourth one, and therefore its return and risk characteristics cannot be fully described and evaluated by the traditional Sharpe based performance measures. This applies to all risk and hedge funds in the sub-sample. Yet, in the case of Seligson Phalanx the effect of higher moments is the most dramatic.

5.5 Mutual fund risk ordering

This section uses different risk proxies for investment risk quantification and calculates their correlation with each other. The aim is to analyse whether risk proxy selection, and therefore return normality have an effect on the risk ordering of Finnish mutual funds. Note that this section focuses solely on the riskiness of the funds, and therefore the reward side is unnoticed.

Finnish equity funds

Panel A in Table 7 presents the correlations of the different risk proxies for the funds investing in Finnish equities. The first interesting observation is the rather weak correlation of Sharpe ratio's standard deviation (denoted as "Sigma" in Table 7) with the other proxies for risk. As mentioned before, in this study the Sharpe ratio's standard deviation is estimated from the excess of a fund return over its relevant benchmark index, whereas the other risk proxies are estimated from the gross return. Secondly, the

VaR-figures at both 1% and 5% level correlate almost perfectly (showing correlation coefficient of 0.99) with all the below-target semi-standard deviation at different target returns indicating that incorporating also skewness into the calculations does not bring any valuable information into our risk analysis for the equity funds investing in Finland. Thirdly, contrary to the other traditional risk proxies, the CFVaR (5%) do not show statistically significant correlation with sigma. This finding hints that the fat-tails of the Finnish equity fund return distributions complicate their risk analysis and their risk levels may be under- or overestimated if we do not incorporate kurtosis into the risk analysis. Further, probability weighted losses (I_1) of Omega at a loss threshold level of (-0.2%) show statistically significant positive correlations with the other risk proxies except with sigma and CFVaR. This suggests that in the Omega framework the loss threshold level of -0.2% may actually depict best the attitudes of Finnish mutual fund investors towards investment risk in 1999-2003. As the loss threshold level of -0.2% implies that investors are willing to accept -0.2% daily net asset value decrease, it corresponds to rather high risk tolerance level. This phenomenon holds for every sub-sample.

Table 7 Risk order correlations: Finnish equity, European equity, global equity funds

This table gives the Spearman correlation coefficients between the risk orderings based on different risk proxies. Correlations are calculated for Finnish mutual funds investing in Finnish equities (Panel A), European equities (Panel B) and global equities (Panel C). R_b - VaR and R_b - CFVaR are estimated at 1% and 5% confidence levels. Semi-standard deviation is estimated using three different exogenously determined target returns of -0.2%, 0.0% and 0.2%. The returns lower than the target return levels are regarded as "bad" volatility, and therefore they are considered the downside risk of an investment. The probability weighted loss (I_1) of Omega is estimated using three exogenously determined loss threshold levels of -0.2%, 0.0% and 0.2%. The returns lower (higher) than the loss threshold levels are regarded as a loss (a gain).

		R_b - VaR		R_b - CFVaR		Semi-stdev.			(I_1)		
	Sigma	1%	5%	1%	5%	-0.2 %	0.0 %	0.2 %	-0.2 %	0.0 %	0.2 %
Panel A: Equity Finland											
Sigma	1***										
R_b - VaR (1%)	0.56**	1***									
R_b - VaR (5%)	0.56**	1***	1***								
R_b - CFVaR (1%)	0.53**	0.76***	0.76***	1***							
R_b - CFVaR (5%)	0.42	0.95***	0.95***	0.60***	1***						
Semi-stdev. (-0.2%)	0.56**	0.99***	0.99***	0.78***	0.95***	1***					
Semi-stdev. (0.0%)	0.57**	0.99***	0.99***	0.78***	0.95***	1***	1***				
Semi-stdev. (0.2%)	0.57**	0.99***	0.99***	0.78***	0.95***	1***	1***	1***			
(I_1) (-0.2%)	0.20	0.59***	0.59***	0.31	0.65	0.59***	0.59***	0.59***	1***		
(I_1) (-0.0%)	-0.19	0.03	0.03	0.33	-0.03	0.01	0.01	0.01	0.18	1***	
(I_1) (0.2%)	-0.09	-0.64***	-0.64***	-0.34	-0.70***	-0.65***	-0.65***	-0.65***	-0.49***	0.24	1***
Panel B: Equity Europe											
Sigma	1***										
R_b - VaR (1%)	0.51	1***									
R_b - VaR (5%)	0.51	1***	1***								
R_b - CFVaR (1%)	0.81***	0.88***	0.88***	1***							
R_b - CFVaR (5%)	0.53	0.99***	0.99***	0.89***	1***						
Semi-stdev. (-0.2%)	0.52	0.99***	0.99***	0.90***	0.99***	1***					
Semi-stdev. (0.0%)	0.52	0.99***	0.99***	0.90***	0.99***	1***	1***				
Semi-stdev. (0.2%)	0.52	0.99***	0.99***	0.90***	0.99***	1***	1***	1***			
(I_1) (-0.2%)	0.12	0.77***	0.77***	0.52	0.79***	0.74**	0.74**	0.74**	1***		
(I_1) (-0.0%)	-0.05	0.48	0.48	0.41	0.50	0.50	0.50	0.50	0.46	1***	
(I_1) (0.2%)	-0.41	-0.51	-0.51	-0.50	-0.49	-0.53	-0.53	-0.53	-0.43	0.26	1***
Panel C: Equity Global											
Sigma	1***										
R_b - VaR (1%)	0.79***	1***									
R_b - VaR (5%)	0.79***	1***	1***								
R_b - CFVaR (1%)	0.76**	0.43	0.43	1***							
R_b - CFVaR (5%)	0.74**	0.96***	0.96***	0.41	1***						
Semi-stdev. (-0.2%)	0.75**	0.94***	0.94***	0.55	0.90***	1***					
Semi-stdev. (0.0%)	0.75**	0.94***	0.94***	0.55	0.90***	1***	1***				
Semi-stdev. (0.2%)	0.75**	0.94***	0.94***	0.55	0.90***	1***	1***	1***			
(I_1) (-0.2%)	0.79***	0.95***	0.95***	0.47	0.87***	0.93***	0.93***	0.93***	1***		
(I_1) (-0.0%)	-0.64**	-0.34	-0.34	-0.69**	-0.40	-0.39	-0.39	-0.39	-0.53	1***	
(I_1) (0.2%)	-0.71**	-0.76**	-0.76**	-0.76**	-0.85***	-0.68**	-0.68**	-0.68**	-0.70**	0.49	1***

*** significant at 1% level, ** significant at 5% level

European equity funds

The riskiness of European equity funds are assessed quite similarly by all the traditional risk proxies and Omega (-0.2%) as shown in Panel B in Table 7. As sigma of the Sharpe ratio is estimated from excess returns, it tends to give somewhat different risk rankings. However, it can be concluded that the investment risk of the Finnish fund with investment focus on European equities can be captured by the variance of a return distribution alone.

Global equity funds

Global equity funds are ranked fairly consistent way with all the risk measures (except with Omega (0.0%) and Omega (0.2%)), only the CFVaR at 1% confidence level disagrees. This results from the extremely fat-tailed return distributions of some globally investing funds in the sub-sample. For example, Nordea Foresta reports an excess kurtosis value of 5.8, and therefore, CFVaR (1%) ranks it the fourth riskiest fund (risk order: eight out of 11) in the sub-sample. Correspondingly, CFVaR (5%) considers the fund the least risky fund in the sub-sample. Therefore, the fat-tails problem seems to be complicating also the risk analysis of the Finnish funds with global investment strategy. We should not only be concerned with incorporating kurtosis into the analysis, but we also have to pay attention to confidence level chosen. In this case the confidence level used seem to have a drastic impact on the results.

Bond funds

Panel D in Appendix 7 documents the values of each risk proxy and their corresponding risk orderings for bond funds. Section 5.3 already reported that the risk-adjusted performance rankings based on the traditional measures are meaningless due to the negative excess returns. Still we can focus on the risk side alone. As reported in Table 3 the bond fund class is the most negatively skewed and the most fat-tailed class in the total sample, which makes the assessment of the riskiness of the bond funds more complex. In fact, Panel D in Table 8 shows that sigma has negative correlation with the majority of other risk proxies, which suggests that variance alone is incapable of capturing the investment risk in Finnish funds investing in European bonds. Further, CFVaR at both significance levels seems to give rather different risk rankings with the others, which gives further evidence on the presence of skewness, peakedness and fat-tails. However, probability weight losses of Omega do not offer convincing evidence that the moments of higher order than four would also affect the riskiness of the seven bond funds under evaluation.

Table 8 Risk order correlations: European bond, Asset allocation, risk and hedge funds

This table gives the Spearman correlation coefficients between the risk orderings based on different risk proxies. Correlations are calculated for Finnish mutual funds investing in European bonds (Panel D). In addition, correlations are calculated for Finnish asset allocation (Panel E) and risk and hedge funds (Panel F). R_b - VaR and R_b - CFVaR are estimated at 1% and 5% confidence levels. Semi-standard deviation is estimated using three different exogenously determined target returns of -0.2%, 0.0% and 0.2%. The returns lower than the target return levels are regarded as "bad" volatility and therefore, they are considered the downside risk of an investment. The probability weighted loss (I_1) of Omega is estimated using three exogenously determined loss threshold levels of -0.2%, 0.0% and 0.2%. The returns lower (higher) than the loss threshold levels are regarded as a loss (a gain).

		R_b - VaR		R_b - CFVaR		Semi-stdev.			(I_1)		
	Sigma	1%	5%	1%	5%	-0.2 %	0.0 %	0.2 %	-0.2 %	0.0 %	0.2 %
Panel D: Bond Europe											
Sigma	1***										
R_b - VaR (1%)	-0.28	1***									
R_b - VaR (5%)	-0.28	1***	1***								
R_b - CFVaR (1%)	0.18	-0.88***	-0.88***	1***							
R_b - CFVaR (5%)	-0.41	0.65**	0.65**	-0.43	1***						
Semi-stdev. (-0.2%)	-0.18	0.93***	0.93***	-0.84***	0.73**	1***					
Semi-stdev. (0.0%)	-0.11	0.93***	0.93***	-0.90***	0.57	0.97***	1***				
Semi-stdev. (0.2%)	-0.32	0.95***	0.95***	-0.82***	0.76**	0.92***	0.88***	1***			
(I_1) (-0.2%)	-0.50	0.69**	0.69**	-0.57	0.91***	0.80***	0.66**	0.76**	1***		
(I_1) (-0.0%)	0.44	-0.09	-0.09	-0.07	-0.39	-0.30	-0.20	-0.16	-0.50	1***	
(I_1) (0.2%)	0.48	-0.68**	-0.68**	0.56	-0.91***	-0.79***	-0.66**	-0.73**	-0.98***	0.35	1***
Panel E: Asset allocation											
Sigma	1***										
R_b - VaR (1%)	0.93**	1***									
R_b - VaR (5%)	0.93**	1***	1***								
R_b - CFVaR (1%)	0.93**	1***	1***	1***							
R_b - CFVaR (5%)	0.93**	1***	1***	1***	1***						
Semi-stdev. (-0.2%)	0.93**	1***	1***	1***	1***	1***					
Semi-stdev. (0.0%)	0.93**	1***	1***	1***	1***	1***	1***				
Semi-stdev. (0.2%)	0.93**	1***	1***	1***	1***	1***	1***	1***			
(I_1) (-0.2%)	0.82**	0.89**	0.89**	0.89**	0.89**	0.89**	0.89**	0.89**	1***		
(I_1) (-0.0%)	-0.14	-0.39	-0.39	-0.39	-0.39	-0.39	-0.39	-0.39	-0.11	1***	
(I_1) (0.2%)	-0.78**	-0.86**	-0.86**	-0.86**	-0.86**	-0.86**	-0.86**	-0.86**	-0.96***	0.04	1***
Panel F: Other											
Sigma	1***										
R_b - VaR (1%)	0.30	1***									
R_b - VaR (5%)	0.30	1***	1***								
R_b - CFVaR (1%)	0.40	0.90	0.90	1***							
R_b - CFVaR (5%)	0.30	1***	1***	0.90	1***						
Semi-stdev. (-0.2%)	0.30	1***	1***	0.90	1***	1***					
Semi-stdev. (0.0%)	0.30	1***	1***	0.90	1***	1***	1***				
Semi-stdev. (0.2%)	0.30	1***	1***	0.90	1***	1***	1***	1***			
(I_1) (-0.2%)	0.25	0.25	0.25	-0.05	0.25	0.25	0.25	0.25	1***		
(I_1) (-0.0%)	0.00	-0.70	-0.70	-0.60	-0.70	-0.70	-0.70	-0.70	-0.65	1***	
(I_1) (0.2%)	0.00	-0.70	-0.70	-0.60	-0.70	-0.70	-0.70	-0.70	-0.65	1***	1***

*** significant at 1% level, ** significant at 5% level

Asset allocation funds

Panel E in Table 8 reports the correlations between the risk orderings according to the different risk proxies for the asset allocation funds. The probability weighted loss of Omega at target return of -0.2% gives statistically significant correlated risk orderings with the traditional risk proxies. Thus, the results suggest that the riskiness of Finnish asset allocation funds can be assessed by variance alone.

Risk and hedge funds

Finally, the results for risk and hedge funds provided in Panel F in Table 8 exhibit very low correlations between the sigma of the Sharpe ratio and all the other risk proxies. The results suggest that the mean-variance framework may be actually incapable in capturing the risk characteristics of risk and hedge funds. Further, the probability weighted loss of Omega at all loss threshold levels shows little or no correlation with all the other risk proxies. This indicates that the Sharpe ratio and its modified forms may not incorporate all the information necessary to assess the riskiness of non-normal risk and hedge fund returns, and the only framework, which is able to cope with this problem, is Omega.

5.6 Asymmetrical investment strategies

This sub-chapter studies the use of asymmetrical investment strategies in the Finnish mutual fund market. In essence, this section examines whether Finnish fund managers have successfully exploited asymmetrical investment strategies such as the short index - short OTM put strategy. As the number of sample funds is rather small in the study, the most applicable and convenient tool for analysing the phenomenon is scatter charts.

This section examines the Driessen and Maenhout (2002) argument that due to the overpriced put options it would be optimal to exploit an investment strategy, which consists of, for example, a short position in some index and a short OTM put position in that particular index. As described in section 2.1.2, an investment strategy of this kind has negatively skewed payout profile. Further, in contrast to Scott and Hovath (1980) argument that investors desire high odd moments, and therefore, high positive skewness, Driessen and Maenhout (2002) argue that due to the put option puzzle this does not hold.

To study this conflict between theories, all the funds are ranked according to their skewness values and compared against the rankings obtained by Sharpe and Omega (-0.2%). The fund with the lowest, or the most negative, skewness value obtains the lowest ranking. The funds are also ranked by their mean return: a high mean value yields a high ranking. Further, as the Sharpe ratio does not incorporate skewness, there should not be any correlation between the rankings based on the Sharpe ratio and the rankings based on skewness. Instead, Omega reacts on the asymmetrical properties of a return distribution. Therefore, assuming that Driessen and Meanhout (2002) argument holds and the Finnish mutual fund managers have used for example the short index – short OTM put strategy successfully, the rankings based on skewness and the rankings based on Omega should be negatively correlated. In a graphic presentation a downward sloping line exhibits negatively correlated parameters.

One issue complicating the analysis in this study is that Omega encompasses all the moments of a return distribution. Therefore, it is impossible to distinguish solely the effect of skewness on performance from the effect of all the other moments. Nevertheless, in Figures 8 and 9 all the sub-samples are ranked according to their mean and skewness values (vertical axis), which are both compared against the rankings based on the Sharpe ratio and the Omega (-0.2%) (horizontal axis). The observation period here is 1999-2003.

Panel A in Figure 8 illustrates the results for the equity funds investing in Finnish companies. It can be observed that the rankings based on the Sharpe and the mean returns are highly correlated with each other. This is not surprising as we recall that the Sharpe ratio is fully defined by the mean excess return divided by its variance. The examination of the relationship between the rankings based on the means and the Sharpe ratio is equivalent to the examination of the relationship between "raw" performance and risk-adjusted performance. The strong correlation between raw performance and risk-adjusted performance is also document in Kasanen and Kinnunen (1990). Further, the rankings based on the means and the Sharpe ratios are highly correlated regardless of the sub-sample. The relationship between the mean rankings and the Omega (-0.2%) rankings is positive, as predicted, but still it is not that straightforward. Panel A shows that a high ranking by mean value does not necessarily imply a high ranking by Omega. This is naturally suggests that we should also be concerned about the investment risk that arises from the higher distributional moments.

Figure 8 Rankings based on mean, skewness, Sharpe and Omega during 1999-2003. Panel (A), Panel (B) and Panel (C).

This figure presents plot charts that exhibit relationships between the fund rankings based on mean, skewness, the Sharpe ratio and the Omega (-0.2%). The observation period is 1999-2003. The plot charts shown are for Finnish mutual funds investing in Finnish equities (Panel A), European equities (Panel B) and global equities (Panel C). High positive mean and skewness values yield high rankings. Also, high Sharpe and Omega values yield high rankings.

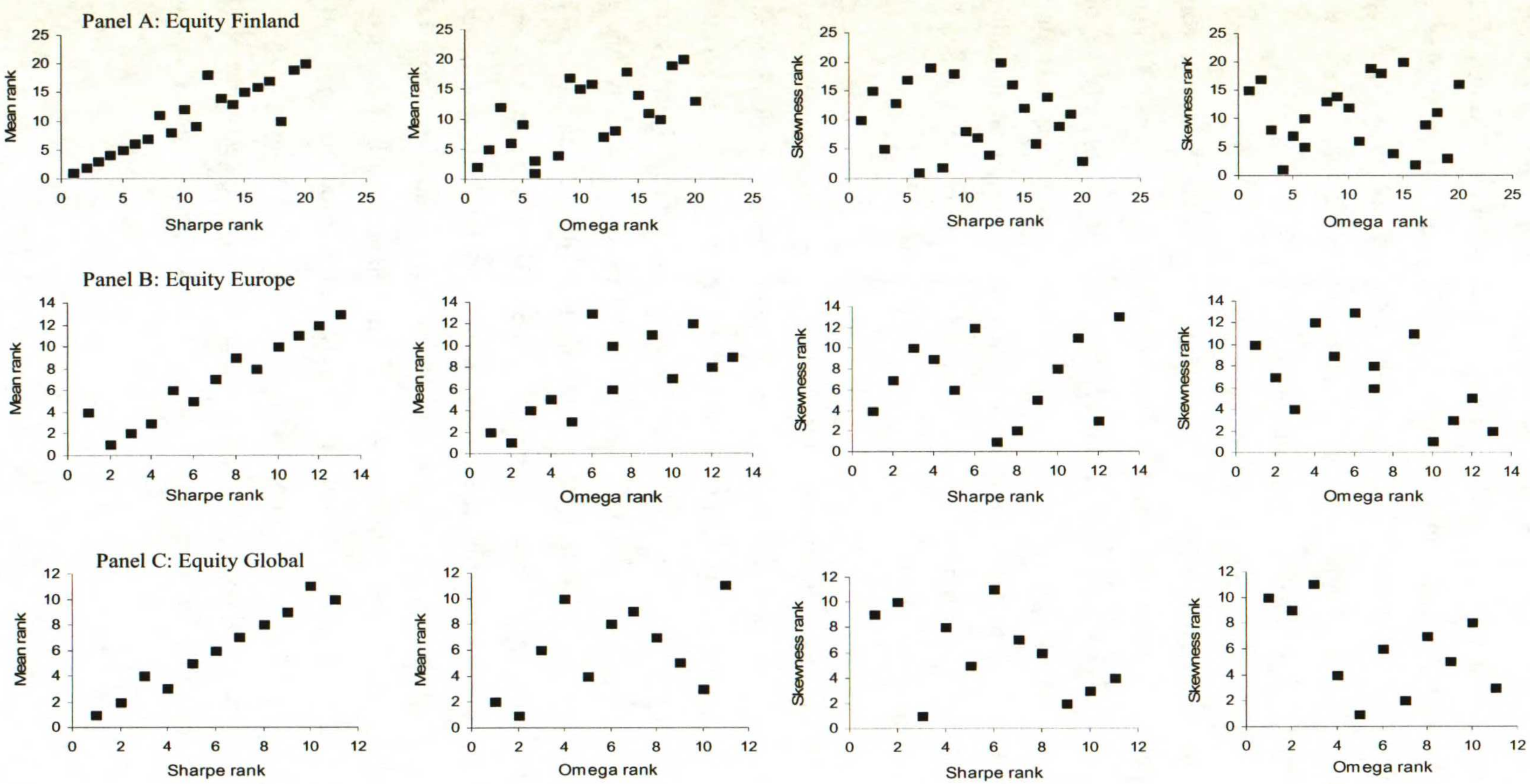
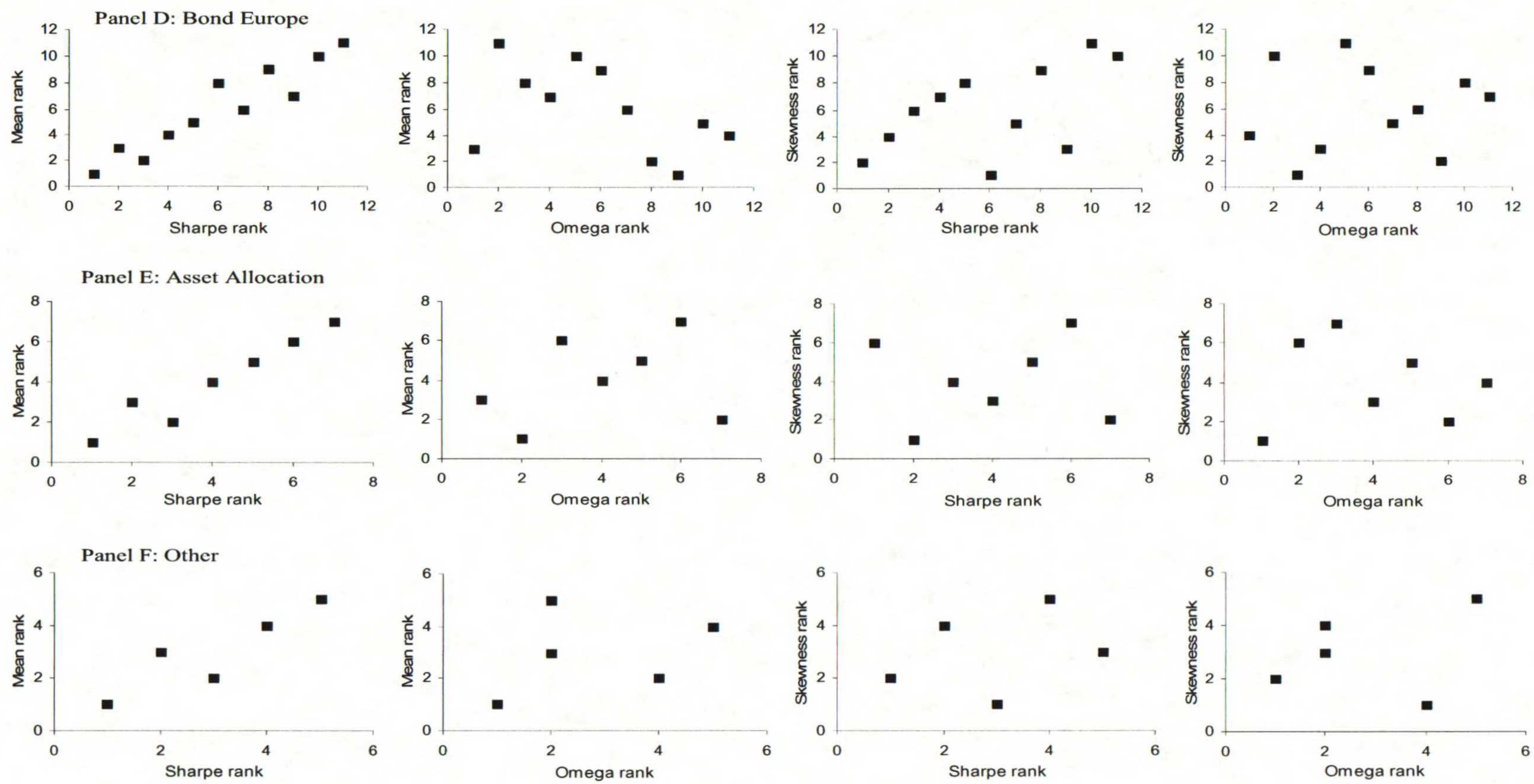


Figure 9 Rankings based on mean, skewness, Sharpe and Omega during 1999-2003. Panel (D), Panel (E) and Panel (F).

This figure presents plot charts that exhibit relationships between the fund rankings based on mean, skewness, the Sharpe ratio and the Omega (-0.2%). The observation period is 1999-2003. The plot charts shown are for Finnish mutual funds investing in European bonds (Panel D). In addition, plot charts are also presented for Finnish asset allocation (Panel E) and risk and hedge funds (Panel F). High positive mean and skewness values yield high rankings. Also, high Sharpe and Omega values yield high rankings.



Moreover, focusing on the rankings based on the skewness values, we find that they do not correlate neither with the Sharpe rankings nor the Omega rankings. This observation does not give any evidence on the view that the Finnish fund managers have used successfully the short index – short OTM put option strategy or some other negatively skewed investment strategy. This can be observed regardless of the sub-sample.

I also took a closer look on year 1999 when all the funds reported high returns and the majority of them reported negative skewness values. Figures 10 and 11 illustrate the rankings based on the mean values and skewness values and compared to the Sharpe and Omega (-0.2%) rankings. We can clearly observe that all sub-samples show high correlation between the mean rankings and the Sharpe rankings. Further, the skewness rankings do not show strong correlation neither with Sharpe rankings nor with Omega rankings. However, the rankings based on skewness and Omega values for Finnish equity funds are negatively correlated. This holds also for the global equity and the risk and the hedge funds, which suggest that negatively skewed investment strategies have been profitable in these fund classes in 1999. However, this rather weak evidence does not support the assumption that the Finnish fund managers would have systemically used negatively skewed strategies in the bullish 1999.

Figure 10 Rankings based on mean, skewness, Sharpe and Omega during 1999-2003. Panel (A), Panel (B) and Panel (C).

This figure presents plot charts that exhibit relationships between the fund rankings based on mean, skewness, the Sharpe ratio and the Omega (-0.2%). The one-year observation period is from January 5th 1999 to December 31st, 1999. The plot charts are shown for Finnish mutual funds investing in Finnish equities (Panel A), European equities (Panel B) and global equities (Panel C). High positive mean and skewness values yield high rankings. Also, high Sharpe and Omega values yield high rankings.

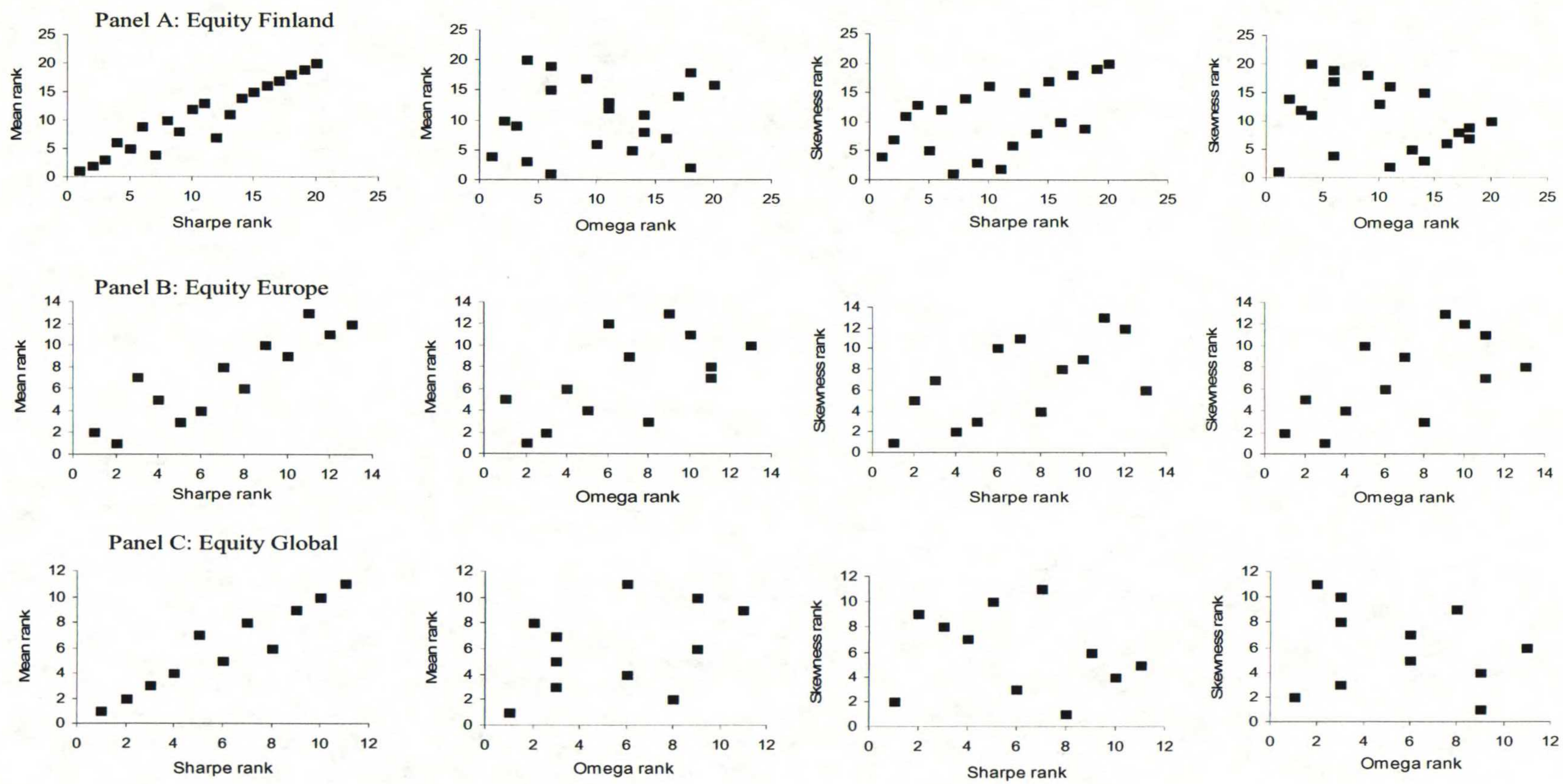
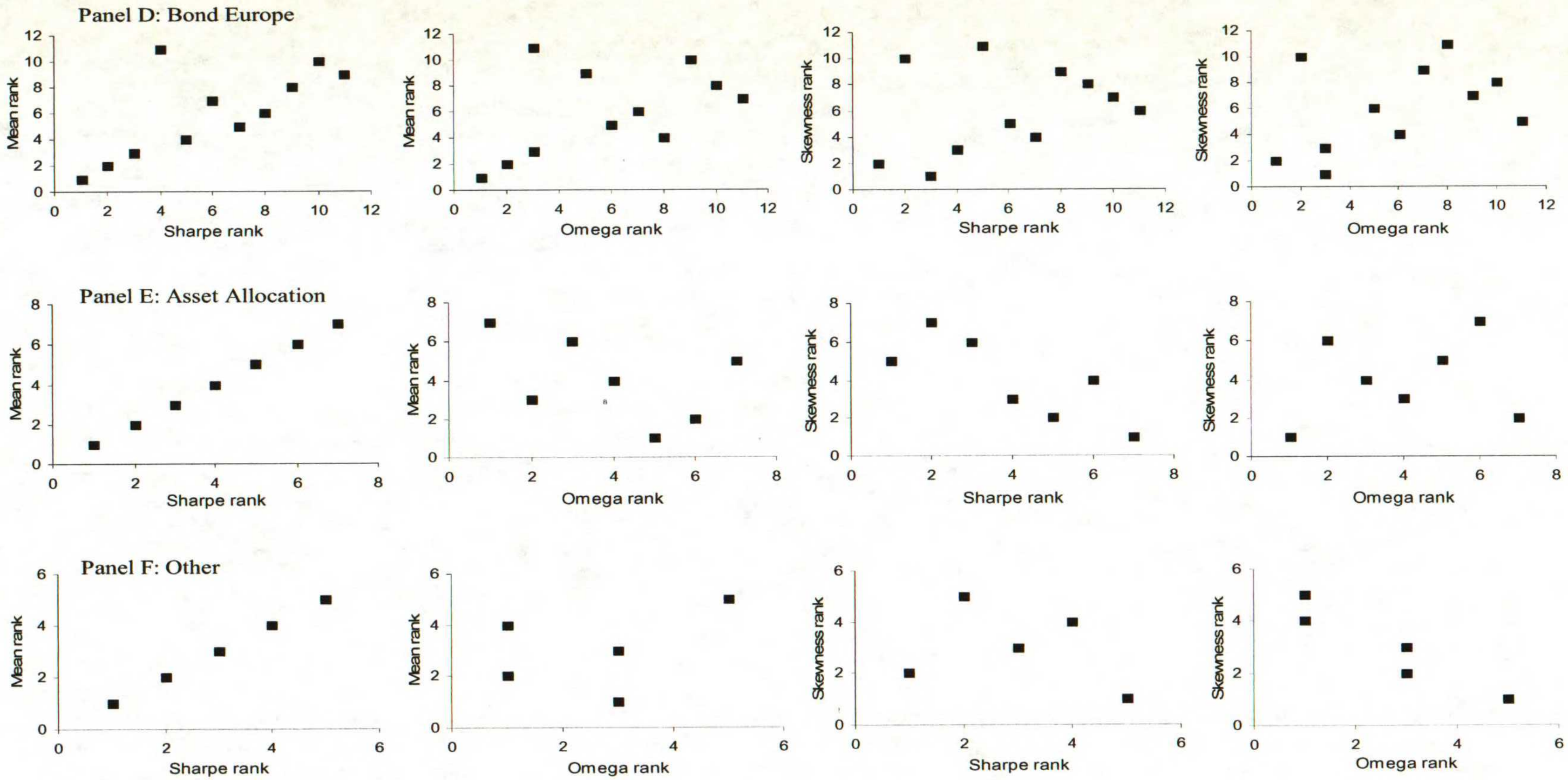


Figure 11 Rankings based on mean, skewness, Sharpe and Omega during 1999. Panel (D), Panel (E) and Panel (F).

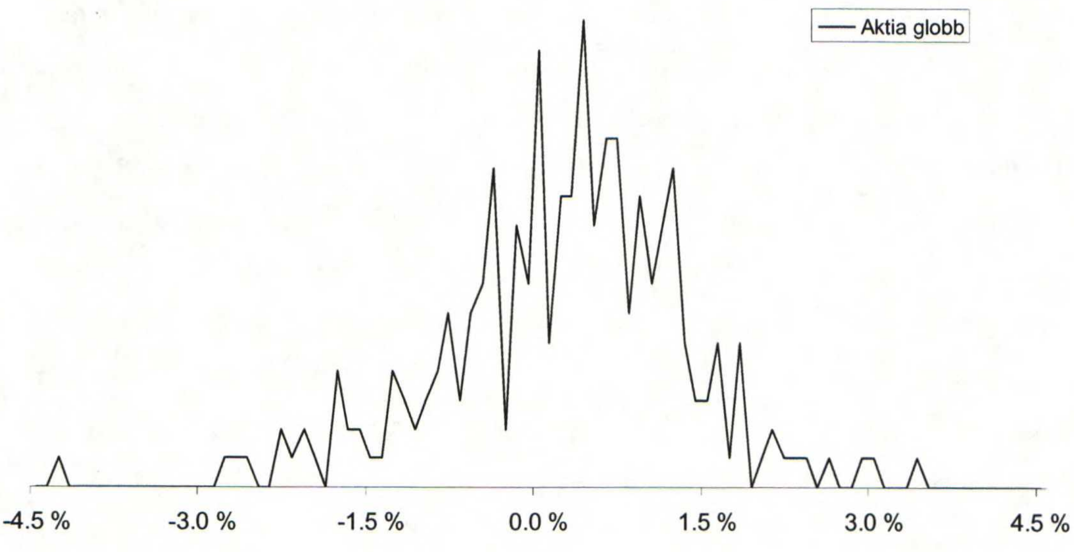
This figure presents plot charts that exhibit relationships between the fund rankings based on mean, skewness, the Sharpe ratio and the Omega (-0.2%). The one-year observation period is from January 5th to December 31st, 1999.The plot charts are shown for Finnish mutual funds investing in European bonds (Panel D). In addition, plot charts are also presented for Finnish asset allocation (Panel E) and risk and hedge funds (Panel F). High positive mean and skewness values yield high rankings. Also, high Sharpe and Omega values yield high rankings.



Although the findings so far do not support the assumption that fund managers have extensively used negatively skewed investment strategies, it is still possible that some fund managers have done so. As we can observe from Figure 12, the fund manager of Aktia Global has taken advantage of negatively skewed investment strategy. In addition, according to the Omega measure, its reward to risk -ratio has been the second best in the sub-sample in 1999. Aktia Global reported the negative skewness value of -0.5, which is the highest negative value among the global equity funds in 1999. In addition, the fund has a low daily mean return value of 0.0016, and therefore the Sharpe ranks it at the 7th place out of 11.

Figure 12 Daily return distribution of Aktia Global in 1999

This figure presents the daily return distribution of Aktia Global in 1999. The number of observations is 251.



5.7 Data frequency, performance evaluation and risk measurement

This section attempts to answer the question whether the frequency of return observations have an effect on performance evaluation and risk measurement. The analysis is conducted by comparing the performance and risk rankings obtained from both daily and weekly returns. Unfortunately, examining the natural investment assessment period of one month is not meaningful since the small number of data points (only 60 data points in the five year time span) would probably yield biased results.

Table 9 reports the correlations between the performance rankings for the total sample calculated from the daily (1254 observations) and weekly (252 observations) returns for each performance measure. The first column provides the correlation coefficient value of 0.994. This means that the rankings, according to the Sharpe ratio, estimated from daily returns correlate at a 99.4% level with that of weekly returns. All the correlations appear to be very high and there are no major differences between the methods. Interestingly, however, all the Omegas exhibit lower correlations than the traditional measures. As Omega uses cumulative density function for assessing the performance and riskiness of a fund, it is extremely important that there are sufficient amount of observations in the analysis to validate the method at each loss threshold level. In this study, the amount of weekly return observations is 252, which may not be sufficient for ranking the funds reliably in the Omega framework. When the performance calculations are conducted by using weekly returns, Omegas do not make any difference between several funds and gives them an equal ranking. This results from the fact that two or more funds get equal ranking if the number of their return observations is equal below a certain loss threshold. If so, the Omega values are equal as well. In general, the data frequency does not seem to have an effect on performance measurement. However, especially in the Omega framework, there should be enough data points to attain robust results. Fvare-Bulle and Pache (2002) find that the sufficient amount of data points for Omega is 100-200. However, the evidence of this study suggests that the adequate number of data points in the Omega framework is more than 250.

Table 9 Correlation between daily and weekly performance rankings

This table shows the Spearman ranking correlation coefficients between daily and weekly level risk-adjusted performance rankings within each evaluation framework. The observation period is 1999-2003. The number of daily and weekly observations are 1254 and 252, respectively. Results are calculated for the total sample of 67 Finnish mutual funds.

	VaR Sharpe		CFVaR Sharpe		R/SV			Omega		
Sharpe	1%	5%	1%	5%	-0.2 %	0.0 %	0.2 %	-0.2 %	0.0 %	0.2 %
0.994***	0.992***	0.992***	0.992***	0.993***	0.992***	0.992***	0.992***	0.983***	0.975***	0.959***

[a] *** significant at 1% level, ** significant at 5% level

Table 10 documents the correlations between risk orderings for the total sample that are estimated from the daily and weekly returns. The results are very well in line with the correlations of the performance measures. These findings suggest that the risk orderings of the Finnish mutual funds of all types are not dependent on the data frequency employed. As long as there are sufficient amount of observations we can safely use both daily and weekly returns to obtain robust results for measuring the riskiness of Finnish mutual funds.

Table 10 Correlation between daily and weekly risk orderings

This table shows the Spearman ranking correlation coefficients between daily and weekly level risk orderings within each evaluation framework. The observation period is 1999-2003. The number of daily and weekly observations are 1254 and 252, respectively. Results are calculated for the total sample of 67 Finnish mutual funds.

	R_b - VaR		R_b - CFVaR		Semi-stdev.			(I_1)		
Sigma	1%	5%	1%	5%	-0.2 %	0.0 %	0.2 %	-0.2 %	0.0 %	0.2 %
0.988***	0.991***	0.991***	0.989***	0.989***	0.991***	0.991***	0.992***	0.983***	0.975***	0.959***

[a] *** significant at 1% level, ** significant at 5% level

6 SUMMARY AND CONCLUSIONS

This chapter answers the research questions presented in chapter 1.2 and discusses them in the context of the existing literature. The answer for the primary research question (question number five) is based on the answers given for the first four research questions.

1) Are Finnish mutual fund returns normally distributed?

In line with Asikainen (2002) paper this study finds that daily returns of Finnish mutual funds are distributed non-normally in a persistent manner during 1999-2003. Further, the majority of Finnish mutual fund returns are non-normal when the observation interval is increased to weekly and monthly observations. However, this study finds that also fund returns show decreasing non-normality as the observation interval increases. This finding is in line with Vaihekoski (1997) study on individual assets. However, the

Jarque-Bera test statistic (29) for normality is sensitive to number of observations. The value of the Jarque-Bera statistic increases as the number of observations increases. Therefore, high frequented data get higher values, which imply increasing non-normality, than low frequented data.

2) *Do the higher distributional moments have an effect on performance evaluation and risk measurement of Finnish mutual funds?*

First of all, the results from the statistics employed in this study should be interpreted very cautiously, because it is extremely difficult to establish when some given impact or distributional characteristics is caused by, say the fourth moment as opposed to all moments of order four or higher[27].

Nevertheless, despite the return non-normality, the empirical findings of this study reveal that the risk-adjusted performance of Finnish mutual funds investing in Finnish and European equities can be well evaluated by the mean-variance framework. All the other frameworks, which include higher moments than mean and variance, rank these funds virtually similarly. In addition, the Finnish asset allocation funds obtain consistent rankings no matter what framework is used. For these reasons, we can conclude that the higher moments than variance do not have a significant effect on risk-adjusted performance measurement of Finnish asset allocation funds nor Finnish funds with investment orientation in Finnish and European equities.

Contrary to the other equity fund classes in the total sample, the empirical evidence on the risk-adjusted performance of globally investing Finnish funds suggests that higher distributional moments complicate their evaluation. In particular, whereas all the traditional frameworks rank the funds identically, the Omega framework disagrees systematically. Therefore, the moments of higher order than kurtosis seem to contain additional information about the risk and reward characteristics of Finnish global equity funds.

[27] For detailed discussion see Keating and Shadwick (2002a).

Further, the results for the small sub-sample of five risk and hedge funds reveal that the mean-variance framework is incapable for measuring their pay-out profiles. In addition, the findings suggest that incorporating either skewness or kurtosis does not convey enough information on crucial aspects of the return distributions. Due to peculiar return distributions of risk and hedge funds, all the distributional moments have to be included to assess their risk-adjusted performance. The finding is in accordance with previous studies by Shadwick and Keating (2002) and Favre-Bulle and Pache (2002).

Due to the incompetence of the traditional performance measurement frameworks to deal with negative excess returns, the majority of the results for Finnish bond funds are meaningless. Therefore, this study cannot make any generalisations about the effect of higher moments on the risk-adjusted performance of Finnish funds investing in European bonds. However, the Omega framework offers relief for this problem by providing an approach which does not suffer from negative excess returns. No matter how badly investments have underperformed their benchmarks, they all can be ranked by Omega.

3) Have Finnish fund managers exploited asymmetrical investment strategies?

All in all, the empirical evidence for the use of negatively skewed investment strategies in the Finnish mutual fund market during 1999-2003 is really weak. In fact, it can be concluded that no evidence was found supporting the systematical use of negatively skewed investment strategies in 1999-2003.

However, this study takes a closer look into the year 1999 when the majority of the funds reported high returns and highly negative skewness values. The results show very weak evidence on that the fund managers of risk and hedge funds would have exploited negatively skewed investment strategies in the bullish 1999. This holds for funds with investment objective in Finnish and global equities as well. Further, there is no evidence that European equity, European bond or asset allocation fund managers would have systematically used these kinds of strategies.

4) *Do data frequency changes have an effect on performance evaluation and risk measurement?*

The performance measurement analysis in this study is performed at both daily and weekly level observations. Unfortunately, the immaturity of Finnish mutual fund market, and the risk and hedge fund market in particular, does not allow using monthly or yearly observations. The observation level used implicitly relates to the time horizon in which investors evaluate risk and return, and therefore monthly and yearly observations would be probably more natural choices than daily and weekly observations. However, using daily and weekly return this study finds strong evidence that the data frequency used does not affect the risk-adjusted performance evaluation of Finnish mutual funds.

5) *Do we need alternative performance evaluation techniques other than the mean-variance framework to assess the performance and the risk levels of Finnish mutual funds of all types?*

The main goal of this paper is to clarify whether the non-normality of Finnish fund returns complicates the assessment of their risk-adjusted performance that we should also be concerned about the higher moments than the two first ones. More particularly, is the non-normality more severe problem in some specified fund market than in some other fund market? Overall, the risk-adjusted performance rankings based on the Reward to semi-variance, the VaR modified- and the CFVaR modified Sharpe ratios did not differ from each other substantially. The finding suggest that these measures do not provide valuable contribution to the information already contained in the Sharpe ratio. Therefore, we can conclude, with certain exceptions, that the third and the fourth central moments, namely skewness and kurtosis, do not have a major effect on the risk-adjusted performance evaluation of Finnish mutual funds. This finding is in accordance with the Asikainen finding in (2002). However, we cannot make straightforward conclusion that only the first two moments matter since the empirical evidence of this study also hints that the higher moments do have an effect on the risk-adjusted performance in some particular cases.

To give better insight into the question, this paper examines funds in different sectors separately. The total sample is divided into six sub-samples according to geographical investment orientation and asset classes. The results based on these six-sub-samples suggest that the traditional mean-variance framework is fairly sufficient for evaluating the risk-adjusted performance of Finnish and European equity funds and asset allocation funds.

However, the results based on a small sub-sample size of five risk and hedge funds suggest that we should also be concerned about the effect of higher distributional moments when evaluating their risk-adjusted performance, and therefore alternative performance measures should be used. Since the risk and hedge fund returns do not show significant negative or positive skewness or excess kurtosis values, their deviations from non-normality are mainly due to the higher distributional moments. Therefore, the payout profiles of risk and hedge funds cannot be evaluated by the Sharpe ratio and its adjusted forms.

Furthermore, the evidence shows that the return distributions of Finnish funds investing in global equities deviate from the Gaussian distribution as well. Thus, the efficiency of the Sharpe ratio and its adjusted forms in evaluating the performance of Finnish funds with investment orientation in global equities can be questioned. Still it should be emphasised that the number of these funds with "very ill-natured" return distributions remains rather small when compared to the scale of total sample.

Further, as the results for bond funds are somewhat contaminated by the negative excess returns during the observation period of 1999-2003, one can not draw meaningful conclusions about their risk-adjusted performance. On the contrary, the rankings obtained by Omega are not sensitive to the sign of returns, which, in turn, supports the use of Omega over the traditional measures.

So, what is the best measure for evaluating risk-adjusted performance? At first sight it seems that the Sharpe ratio functions adequately in most cases. In addition, the Sharpe ratio is already the most popular portfolio performance measure and fairly easy to calculate. However, there are clearly cases in which we cannot base our investment decision solely on the information that is obtained from mean and variance only. We need to be concerned about the higher moments as well. And if we need to be interested in the higher moments than variance the results suggest that we incorporate directly all the distributional moments not just the third and the fourth ones. Therefore, the study concludes that the Omega measure should be employed alongside with the Sharpe ratio if we have reason to believe that the higher moments are also present complicating our evaluation process. To conclude, Table 11 gives my recommendations on the question what performance measures should be employed for evaluating sufficiently the risk and reward characteristics of each fund class. In addition, whenever the estimated excess returns are negative, the best framework is Omega regardless of the fund type.

Table 11 Performance measure recommendations

This table summarises the recommendations for sufficient risk-adjusted performance measures for each Finnish mutual fund class. Table also reports the size of each sub-sample on which the results are based.

Fund class	Sample size	Performance measure recommendation
Finnish Equity	20	Sharpe
European Equity	13	Sharpe
Global Equity	11	Sharpe + Omega
Bond Europe	11	Sharpe
Asset Allocation	7	Sharpe
Other	5	Sharpe + Omega

It must be noted, however, that the level of the loss threshold selected has a critical influence on the rankings in the Omega framework. This, in turn, implies that the attractiveness of a fund is principally determined by the individual loss aversion level of an investor.

This study reports that Finnish mutual funds are non-normally distributed. In addition, this study tries to find reasons for the non-normality. In particular, this study examines whether the best performing funds have exploited negatively skewed investment strategies. However, the results show that excellent fund performance cannot be explained by this theory alone. Accordingly, as we now have more robust tools for performance measurement, this study suggests that future research should focus on finding and quantifying the determinants of fund performance.

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Appendix 1 Fund abbreviations, full names and classes

Fund Abbreviation	Fund Name	Fund Class
ABERGFINB	Alfred Berg Finland	Equity Finland
ABERGOPTIB	Alfred Berg Optimal	Asset Allocation
AKTIACAPB	Aktia Capital	Equity Finland
AKTIAEUROB	Aktia Euro	Equity Europe
AKTIAGLOBB	Aktia Global	Equity Global
ALBEUBOB	Ålandsbanken Euro Bond	Bond Europe
ALBGLOBLUB	Ålandsbanken Global Value	Equity Global
ALFEUOBLB	Alfred Berg Euro Obligaatio	Bond Europe
ALFPFOLIOB	Alfred Berg Portfolio	Equity Finland
CARNEGIOSA	Carnegie Suomi Osake	Equity Finland
CONFOCUSB	Conventum Focus (now Pohjola Focus)	Other
CONKOROSB	Conventum Korko+Osake (now Pohjola Korko+Osake)	Asset Allocation
EQARVONKAA	EQ Arvonkasvattajat	Equity Europe
EVLIESCB	Evli European Smaller Companies	Equity Europe
EVLIEU50B	Evli Euro 50	Equity Europe
EVLIEUOBLB	Evli Euro Government Bond	Bond Europe
EVLIEUYHKB	Evli Target Return	Bond Europe
EVLIGLOBAB	Evli Global	Equity Global
EVLIMIXB	Evli Euro Mix	Asset Allocation
EVLISELECB	Evli Select	Equity Finland
FIMEURO	FIM Euro	Bond Europe
FIMFENNO	FIM Fenno	Equity Finland
FIMTEKNO	FIM Tekno	Equity Global
FONDITA20B	Fondita 2000+	Equity Global
FONDITAEQB	Fondita Equity Spice	Equity Finland
GYLLEUEQUB	Gyllenberg European Equity Value	Equity Europe
GYLLFINLB	Gyllenberg Finlandia	Equity Finland
GYLLMOMENB	Gyllenberg Momentum	Other
GYLLOPTIMB	Gyllenberg Optimum	Asset Allocation
GYLLSFIRMB	Gyllenberg Small Firm	Equity Finland
HANOBLIGA	Handelsbanken Euro-Obligaatio	Bond Europe
HANOSAKE	Handelsbanken Osake	Equity Finland
MANDEUGROK	Mandatum European Growth	Equity Europe
MANDGLOBAK	Mandatum Global	Equity Global
MANDGLOTEK	Mandatum Global Tech	Equity Global
MANDKONTRK	Mandatum Kontra	Other
MANDNEUTRK	Mandatum Neutral	Asset Allocation
MANDSKASVK	Mandatum Suomi Kasvuosake	Equity Finland
MANDVIPUK	Mandatum Vipu	Other
NEUROLANDK	Nordea Euroland	Equity Europe
NEUROPAK	Nordea Eurooppa.fi	Equity Europe
NFENNIAK	Nordea Fennia	Equity Finland
NFENNIAPLK	Nordea Fennia Plus	Equity Finland
NFORESTAK	Nordea Foresta	Equity Global
NPROEOBLK	Nordea Pro Euro Obligaatio	Bond Europe
NPROSUOMIK	Nordea Pro Finland	Equity Finland
OPDELTAA	Op-Delta	Equity Finland
OPEUOSAKEA	Op-Euro Osake	Equity Europe
OPMETSAA	Op-Metsä	Equity Global
OPPIRKKAA	Op-Pirkka	Asset Allocation
OPSGLOEQA	Opstock Global Equity	Equity Global
PHALANXA	Seligson Phalanx	Other
POHEKASVB	Pohjola Euro Kasvu	Equity Europe
POHFINKB	Pohjola Finland Kasvu	Equity Finland
POHFINVB	Pohjola Finland Value	Equity Finland
POHFORTEB	Pohjola Forte	Asset allocation
POHOBLIB	Pohjola Obligaatio	Bond Europe
SAMPOEUOSK	Sampo Euroopa Osake	Equity Europe
SAMPOEUVAK	Sampo Euro Value	Equity Europe
SAMPOOBLIK	Sampo Obligaatio	Bond Europe
SAMPOSOSAK	Sampo Suomi Osake	Equity Finland
SAMPOSYOSK	Sampo Suomi Yhteisöosake	Equity Finland
SAMPOYOBLK	Sampo Yhteisöobligaatio	Bond Europe
SELEUROBLA	Seligson Euro Obligaatioindeksirahasto	Bond Europe
SELGLOBALA	Seligson Global Top 25 Brands	Equity Global
SELIGEU50A	Seligson Eurooppa 50-Indenksirahasto	Equity Europe
SELIGFOXA	Seligson & Co HEX 25 -Indeksirahasto	Equity Finland

Appendix 2 Performance measures and ranking orders: Equity Finland (Panel A)

This table reports performance measure values and their corresponding ranking orders for Finnish mutual funds investing in Finnish equities. All the performance measures are estimated from daily returns during observation period of 1999-2003. High performance measure value yields high ranking, i.e. the fund with highest performance value gets the first position. The VaR modified Sharpe ratio and the CFVaR modified Sharpe are estimated at significance levels of 5% and 1%. The Reward to semi-variance is estimated using three different target return levels of -0.2%, 0.0% and 0.2%. In the Reward to semi-variance framework investment risk arises from not achieving the specified target return. The Omega is calculated at loss thresholds levels of -0.2%, 0.0% and 0.2%. In the Omega framework all the return outcomes below the specified loss threshold level are regarded as a loss and all the return outcomes above the loss threshold are regarded as a gain. Therefore, the loss threshold level chosen refers to investor's preference towards risk: the lower the loss threshold, the less risk averse the investor.

	Sharpe		VaR mod Sharpe				CFVaR mod Sharpe				Reward to semi-variance						Omega					
			1%		5%		1%		5%		-0.2 %		0.0 %		0.2 %		-0.2 %		0.0 %		0.2 %	
	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank
Panel A: Equity Finland																						
Abergfinb	0.013	17	0.003	17	0.005	17	0.002	17	0.005	17	0.012	17	0.012	17	0.012	17	1.473	9	1.158	3	0.833	10
Aktiacapb	0.047	5	0.021	3	0.030	3	0.015	3	0.029	3	0.078	3	0.078	3	0.077	3	1.738	2	1.093	10	0.751	19
Alfpfoliob	0.015	15	0.004	16	0.006	16	0.003	16	0.005	16	0.014	16	0.014	16	0.014	16	1.469	10	1.155	5	0.844	8
Carnegieosa	0.015	16	0.004	15	0.006	15	0.003	14	0.006	14	0.015	14	0.015	14	0.015	14	1.454	11	1.083	12	0.828	11
Evliselecb	0.026	9	0.007	8	0.010	8	0.005	8	0.009	9	0.025	8	0.025	8	0.025	8	1.430	13	1.063	17	0.874	5
Finfenno	0.092	1	0.025	2	0.036	2	0.017	2	0.035	2	0.094	2	0.094	2	0.094	2	1.498	6	1.083	12	0.828	11
Fonditaeqb	0.052	3	0.015	4	0.021	4	0.012	4	0.020	4	0.054	4	0.055	4	0.054	4	1.498	6	1.166	2	0.894	3
Gyllfinlb	0.034	7	0.009	7	0.012	7	0.006	7	0.012	7	0.032	7	0.032	7	0.031	7	1.435	12	1.118	6	0.855	6
Gyllsfirmb	0.019	11	0.007	9	0.010	9	0.004	12	0.010	8	0.025	9	0.025	9	0.025	9	1.518	5	1.083	12	0.766	17
Hanosake	0.022	10	0.005	12	0.008	12	0.004	11	0.007	12	0.020	12	0.020	12	0.020	12	1.570	3	0.756	20	0.756	18
Mandskasvk	-0.019	20	-0.006	20	-0.009	20	-0.004	20	-0.009	20	-0.023	20	-0.023	20	-0.023	20	1.366	19	1.076	16	0.850	7
Nfenniak	0.018	12	0.003	18	0.004	18	0.002	18	0.004	18	0.012	18	0.012	18	0.012	18	1.426	14	1.087	11	0.810	15
Nfenniaplk	0.037	6	0.010	6	0.014	6	0.006	6	0.016	6	0.038	6	0.039	6	0.038	6	1.564	4	1.042	19	0.820	14
Nprosuomik	0.032	8	0.006	11	0.008	11	0.005	9	0.008	11	0.022	11	0.022	11	0.022	11	1.407	16	1.056	18	0.802	16
Opdeltaa	0.048	4	0.013	5	0.018	5	0.010	5	0.018	5	0.047	5	0.047	5	0.047	5	1.488	8	1.158	3	0.903	1
Pohfinkb	0.017	13	0.004	13	0.006	13	0.003	13	0.006	13	0.016	13	0.016	13	0.016	13	1.412	15	1.111	7	0.880	4
Pohfinvb	0.068	2	0.045	1	0.063	1	0.028	1	0.063	1	0.169	1	0.170	1	0.167	1	2.167	1	1.268	1	0.747	20
Sampososak	0.004	19	0.002	19	0.003	19	0.002	19	0.003	19	0.008	19	0.008	19	0.008	19	1.398	18	1.104	8	0.825	13
Samposyosk	0.012	18	0.006	10	0.009	10	0.004	10	0.008	10	0.022	10	0.022	10	0.022	10	1.402	17	1.101	9	0.839	9
Seligfoxa	0.015	14	0.004	14	0.006	14	0.003	15	0.005	15	0.015	15	0.015	15	0.015	15	1.362	20	1.080	15	0.897	2

Appendix 3 Performance measures and ranking order: Equity Europe (Panel B) and Equity Global (Panel C)

This table reports performance measure values and their corresponding ranking orders for Finnish mutual funds investing in European equities (Panel B) and global equities (Panel C). All the performance measures are estimated from daily returns during observation period of 1999-2003. High performance measure value yields high ranking, i.e. the fund with highest performance value gets the first position. The VaR modified Sharpe ratio and the CFVaR modified Sharpe are estimated at significance levels of 5% and 1%. The Reward to semi-variance is estimated using three different target return levels of -0.2%, 0.0% and 0.2%. In the Reward to semi-variance framework investment risk arises from not achieving the specified target return. The Omega is calculated at loss thresholds levels of -0.2%, 0.0% and 0.2%. In the Omega framework all the return outcomes below the specified loss threshold level are regarded as a loss and all the return outcomes above the loss threshold are regarded as a gain. Therefore, the loss threshold level chosen refers to investor's preference towards risk: the lower the loss threshold, the less risk averse the investor.

	Sharpe		VaR mod Sharpe				CFVaR mod Sharpe				Reward to semi-variance						Omega					
			1%		5%		1%		5%		-0.2 %		0.0 %		0.2 %		-0.2 %		0.0 %		0.2 %	
	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank
Panel B: Equity Europe																						
Aktiaeurob	0.015	6	0.006	5	0.008	5	0.004	6	0.008	5	0.021	5	0.021	5	0.021	5	1.528	4	0.994	11	0.791	7
Egarvonkaa	0.042	2	0.019	1	0.027	1	0.015	1	0.028	1	0.073	1	0.073	1	0.073	1	1.618	2	1.069	2	0.789	8
Evliescb	0.036	3	0.015	2	0.022	2	0.010	2	0.022	2	0.055	2	0.056	2	0.055	2	1.818	1	1.029	5	0.706	13
Evlieu50b	0.008	8	0.001	8	0.002	8	0.001	8	0.002	8	0.004	8	0.004	8	0.004	8	1.235	13	0.975	12	0.799	6
Gylleuequb	0.049	1	0.010	3	0.015	3	0.008	3	0.015	3	0.038	3	0.038	3	0.038	3	1.538	3	1.059	4	0.771	10
Mandeugrok	-0.026	13	-0.010	13	-0.015	13	-0.007	13	-0.014	13	-0.036	13	-0.036	13	-0.036	13	1.389	6	1.010	10	0.781	9
Neurolandk	0.018	5	0.005	6	0.007	6	0.004	5	0.007	6	0.018	6	0.018	6	0.018	6	1.371	7	1.063	3	0.823	3
Neuropak	0.011	7	0.003	7	0.004	7	0.003	7	0.004	7	0.011	7	0.011	7	0.011	7	1.331	10	1.026	7	0.756	11
Opeuosakea	0.003	9	0.001	9	0.001	9	0.001	9	0.001	9	0.004	9	0.004	9	0.004	9	1.305	12	1.016	8	0.833	2
Pohekasvb	-0.020	12	-0.007	12	-0.010	12	-0.006	12	-0.010	12	-0.026	12	-0.026	12	-0.026	12	1.314	11	1.013	9	0.815	4
Sampoeuosk	0.001	11	0.000	11	0.000	11	0.000	11	0.000	11	0.001	11	0.001	11	0.001	11	1.340	9	1.029	5	0.815	4
Sampoeuvak	0.024	4	0.009	4	0.013	4	0.007	4	0.013	4	0.033	4	0.033	4	0.033	4	1.430	5	1.115	1	0.850	1
Seligeu50a	0.002	10	0.001	10	0.001	10	0.000	10	0.001	10	0.002	10	0.002	10	0.002	10	1.371	7	0.759	13	0.756	11
Panel C: Equity Global																						
Aktiaglobb	0.006	6	0.002	6	0.003	6	0.001	6	0.003	6	0.008	6	0.008	6	0.008	6	1.430	3	0.984	9	0.764	8
Albgloblub	-0.023	11	-0.009	11	-0.012	11	-0.007	11	-0.012	11	-0.032	11	-0.032	11	-0.032	11	1.421	4	0.994	7	0.756	10
Evliglobab	-0.009	9	-0.004	9	-0.005	9	-0.003	9	-0.005	9	-0.014	9	-0.014	9	-0.014	9	1.366	7	0.889	10	0.732	11
Fimtekno	0.006	5	0.002	5	0.003	5	0.002	5	0.003	5	0.009	5	0.009	5	0.009	5	1.309	9	1.023	6	0.866	1
Fondita20b	0.016	4	0.006	4	0.008	4	0.004	4	0.008	4	0.022	4	0.022	4	0.022	4	1.305	10	1.029	1	0.823	4
Mandglobak	0.004	7	0.002	7	0.002	7	0.001	7	0.002	7	0.006	7	0.006	7	0.006	7	1.335	8	1.026	4	0.825	3
Mandglotek	-0.015	10	-0.006	10	-0.009	10	-0.006	10	-0.009	10	-0.023	10	-0.023	10	-0.023	10	1.216	11	1.029	1	0.858	2
Nforestak	0.034	1	0.016	1	0.023	1	0.010	1	0.023	1	0.062	1	0.062	1	0.061	1	1.435	2	1.029	1	0.769	7
Opemetsaa	0.033	2	0.014	2	0.020	2	0.009	2	0.019	2	0.052	2	0.052	2	0.052	2	1.440	1	0.994	7	0.761	9
Opsgloeqa	0.004	8	0.002	8	0.002	8	0.001	8	0.002	8	0.006	8	0.006	8	0.006	8	1.398	6	1.026	4	0.784	5
Selglobala	0.017	3	0.007	3	0.010	3	0.006	3	0.010	3	0.027	3	0.027	3	0.027	3	1.407	5	0.779	11	0.776	6

Appendix 4 Performance measures and ranking orders: Bond Europe (Panel D), Asset Allocation (Panel E) and Other (Panel F)

This table reports performance measure values and their corresponding ranking orders for Finnish mutual funds investing in European bonds (Panel D). In addition, performance measures and rankings are reported for Finnish Asset Allocation (Panel E) and risk and hedge funds (Panel F). All the performance measures are estimated from daily returns during observation period of 1999-2003. High performance measure value yields high ranking, i.e. the fund with highest performance value gets the first position. The VaR modified Sharpe ratio and the CFVaR modified Sharpe are estimated at significance levels of 5% and 1%. The Reward to semi-variance is estimated using three different target return levels of -0.2%, 0.0% and 0.2%. In the Reward to semi-variance framework investment risk arises from not achieving the specified target return. The Omega is calculated at loss thresholds levels of -0.2%, 0.0% and 0.2%. In the Omega framework all the return outcomes below the specified loss threshold level are regarded as a loss and all the return outcomes above the loss threshold are regarded as a gain. Therefore, the loss threshold level chosen refers to investor's preference towards risk: the lower the loss threshold, the less risk averse the investor.

			VaR mod Sharpe				CFVaR mod Sharpe				Reward to semi-variance						Omega					
	Sharpe		1%		5%		1%		5%		-0.2 %		0.0 %		0.2 %		-0.2 %		0.0 %		0.2 %	
	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank
Panel D: Bond Europe																						
Albeubob	-0.010	2	-0.042	10	-0.057	10	-0.033	10	-0.056	10	-0.390	11	-0.200	11	-0.116	10	208.0	1	0.789	10	0.005	11
Alfeuoblb	-0.011	5	-0.014	4	-0.020	4	-0.012	4	-0.019	4	-0.056	4	-0.056	4	-0.047	3	5.302	10	1.223	1	0.238	3
Evlieuoblb	-0.011	4	-0.014	3	-0.020	3	-0.012	5	-0.019	3	-0.056	3	-0.056	3	-0.047	4	4.887	11	1.049	4	0.273	1
Evlieuyhkb	-0.013	11	-0.043	11	-0.059	11	-0.035	11	-0.055	9	-0.250	10	-0.184	10	-0.117	11	38.19	2	0.889	7	0.018	10
Fimeuro	-0.011	6	-0.015	5	-0.021	5	-0.003	1	-0.089	11	-0.061	5	-0.061	5	-0.052	6	7.708	3	0.883	8	0.169	9
Hanobliga	-0.011	7	-0.016	6	-0.022	6	-0.013	6	-0.021	5	-0.064	6	-0.064	6	-0.052	7	5.431	7	1.219	3	0.231	4
Nproeoblk	-0.012	9	-0.016	7	-0.022	7	-0.014	8	-0.022	6	-0.066	7	-0.065	7	-0.052	5	6.789	4	0.841	9	0.198	8
Pohoblib	-0.010	3	-0.014	2	-0.019	2	-0.012	3	-0.018	2	-0.055	2	-0.055	2	-0.045	2	5.398	8	1.039	5	0.229	5
Sampooblik	-0.013	10	-0.020	9	-0.027	9	-0.016	9	-0.026	8	-0.076	9	-0.076	9	-0.063	9	6.125	5	1.223	1	0.214	7
Sampoyoblk	-0.011	8	-0.017	8	-0.024	8	-0.014	7	-0.022	7	-0.067	8	-0.067	8	-0.055	8	5.967	6	1.029	6	0.220	6
Seleurobla	-0.009	1	-0.009	1	-0.012	1	-0.008	2	-0.012	1	-0.034	1	-0.034	1	-0.034	1	5.333	9	0.263	11	0.242	2
Panel E: Asset Allocation																						
Abergoptib	0.019	6	0.012	5	0.018	5	0.008	6	0.017	5	0.044	6	0.044	6	0.044	6	1.768	3	1.090	1	0.665	5
Conkorosb	0.012	7	0.006	7	0.009	7	0.005	7	0.009	7	0.024	7	0.024	7	0.024	7	1.483	6	0.784	5	0.784	2
Elvimixb	0.024	4	0.018	3	0.025	3	0.013	3	0.025	3	0.065	3	0.065	3	0.065	3	1.662	4	0.749	6	0.749	3
Gylloptmb	0.021	5	0.014	4	0.020	4	0.011	4	0.020	4	0.053	4	0.053	4	0.052	4	1.657	5	1.010	4	0.668	4
Mandneutrk	0.027	2	0.193	1	0.285	1	0.115	1	1.700	1	1.981	1	0.882	1	0.530	1	208.0	1	0.688	7	0.027	7
Opppirkkaa	0.024	3	0.012	6	0.017	6	0.009	5	0.017	6	0.045	5	0.045	5	0.045	5	1.469	7	1.073	3	0.794	1
Pohforteb	0.033	1	0.027	2	0.038	2	0.021	2	0.037	2	0.098	2	0.100	2	0.098	2	2.014	2	1.083	2	0.663	6
Panel F: Other																						
Confocusb	-0.026	5	-0.009	5	-0.013	5	-0.008	5	-0.013	5	-0.035	5	-0.035	5	-0.035	5	1.314	2	1.036	3	0.850	3
Gyllmomenb	0.009	2	0.004	3	0.005	3	0.002	3	0.005	3	0.013	3	0.013	3	0.013	3	1.314	2	1.076	2	0.861	2
Mandkontrk	0.008	3	0.006	2	0.009	2	0.006	2	0.009	2	0.024	2	0.024	2	0.024	2	1.305	4	0.872	4	0.704	4
Mandvipuk	-0.009	4	-0.003	4	-0.005	4	-0.002	4	-0.004	4	-0.012	4	-0.012	4	-0.012	4	1.301	5	1.080	1	0.872	1
Phalanxa	0.023	1	0.023	1	0.032	1	0.017	1	0.034	1	0.087	1	0.087	1	0.087	1	1.965	1	0.522	5	0.505	5

Appendix 5 Risk proxies and ranking orders: Equity Finland (Panel A)

This table reports risk proxy values and their corresponding ranking orders for Finnish mutual funds investing in Finnish equities. All the risk proxies are estimated from daily returns during observation period of 1999-2003. High risk proxy value yields low ranking, i.e. the riskiest fund gets the last position. Sigma of the Sharpe ratio is estimated from the excess returns distributions. All the other risk proxies are estimated from the gross return distributions. R_b - VaR and R_b - CFVaR are estimated at significance levels of 5% and 1%. The semi-standard deviation is estimated using three different target return levels of -0.2%, 0.0% and 0.2%. In the Reward to semi-variance framework investment risk arises from not achieving the specified target return. The probability weighted losses (I_l) of Omega is calculated at loss thresholds levels of -0.2%, 0.0% and 0.2%. In the Omega framework all the return outcomes below the specified loss threshold level are regarded as a loss and all the return outcomes above the loss threshold are regarded as a gain. Therefore, the loss threshold level chosen refers to investor's preference towards risk: the lower the loss threshold, the less risk

	Sigma		R_b - VaR				R_b - CFVaR				Semi-stdev.						(I_l)					
			1%		5%		1%		5%		-0.2 %		0.0 %		0.2 %		-0.2 %		0.0 %		0.2 %	
	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank
Panel A: Equity Finland																						
Abergfinb	0.011	14	0.041	18	0.029	18	0.055	16	0.030	18	0.011	18	0.011	18	0.011	18	0.404	9	0.463	3	0.545	10
Aktiacapb	0.010	8	0.022	2	0.015	2	0.030	2	0.016	2	0.006	2	0.006	2	0.006	2	0.365	2	0.478	10	0.571	19
Alfpfoliob	0.011	13	0.040	17	0.029	17	0.053	11	0.029	17	0.011	17	0.011	17	0.011	17	0.405	10	0.464	5	0.542	8
Carnegieosa	0.010	4	0.035	8	0.025	8	0.044	6	0.025	9	0.010	7	0.009	7	0.010	7	0.407	11	0.480	12	0.547	11
Evliselecb	0.010	11	0.039	16	0.028	16	0.055	15	0.029	16	0.011	16	0.011	16	0.011	16	0.411	13	0.485	17	0.533	5
Finfenno	0.010	12	0.037	11	0.026	11	0.054	13	0.027	10	0.010	10	0.010	10	0.010	10	0.400	6	0.480	12	0.547	11
Fonditaeqb	0.010	5	0.034	5	0.024	5	0.043	4	0.025	7	0.009	5	0.009	5	0.009	5	0.400	6	0.462	2	0.528	3
Gyllfinlb	0.010	6	0.038	13	0.027	13	0.054	14	0.028	15	0.010	14	0.010	14	0.010	14	0.411	12	0.472	6	0.539	6
Gyllsfirmb	0.012	17	0.035	7	0.025	7	0.059	19	0.024	5	0.010	9	0.010	9	0.010	9	0.397	5	0.480	12	0.566	17
Hanosake	0.008	3	0.035	6	0.024	6	0.045	7	0.025	8	0.009	6	0.009	6	0.009	6	0.389	3	0.569	20	0.569	18
Mandskasvk	0.017	18	0.050	20	0.036	20	0.073	20	0.035	20	0.014	20	0.014	20	0.014	20	0.423	19	0.482	16	0.541	7
Nfenniak	0.006	1	0.033	3	0.024	3	0.043	3	0.024	4	0.009	3	0.009	3	0.009	3	0.412	14	0.479	11	0.553	15
Nfenniaplk	0.010	9	0.036	9	0.026	9	0.057	18	0.023	3	0.010	8	0.010	8	0.010	8	0.390	4	0.490	19	0.549	14
Nprosuomik	0.006	2	0.034	4	0.024	4	0.043	5	0.024	6	0.009	4	0.009	4	0.009	4	0.415	16	0.486	18	0.555	16
Opdeltaa	0.010	10	0.037	12	0.026	12	0.050	8	0.027	12	0.010	12	0.010	12	0.010	12	0.402	8	0.463	3	0.526	1
Pohfinkb	0.010	7	0.036	10	0.026	10	0.050	9	0.027	11	0.010	11	0.010	11	0.010	11	0.415	15	0.474	7	0.532	4
Pohfinvb	0.012	16	0.018	1	0.013	1	0.028	1	0.013	1	0.005	1	0.005	1	0.005	1	0.316	1	0.441	1	0.573	20
Sampososak	0.019	19	0.038	14	0.027	14	0.051	10	0.028	13	0.010	13	0.010	13	0.010	13	0.417	18	0.475	8	0.548	13
Samposyosk	0.020	20	0.039	15	0.027	15	0.054	12	0.028	14	0.011	15	0.011	15	0.011	15	0.416	17	0.476	9	0.544	9
Seligfoxa	0.011	15	0.043	19	0.031	19	0.057	17	0.032	19	0.012	19	0.012	19	0.012	19	0.423	20	0.481	15	0.527	2

Appendix 6 Risk proxies and ranking orders: Equity Europe (Panel B) and Equity Global (Panel C)

This table reports risk proxy values and their corresponding ranking orders for Finnish mutual funds investing in European equities (Panel B) and global equities (Panel C). All the risk proxies are estimated from daily returns during observation period of 1999-2003. High risk proxy value yields low ranking, i.e. the riskiest fund gets the last position. Sigma of the Sharpe ratio is estimated from the excess returns distributions. All the other risk proxies are estimated from the gross return distributions. R_b - VaR and R_b - CFVaR are estimated at significance levels of 5% and 1%. The semi-standard deviation is estimated using three different target return levels of -0.2%, 0.0% and 0.2%. In the Reward to semi-variance framework investment risk arises from not achieving the specified target return. The probability weighted losses (I_l) of Omega is calculated at loss thresholds levels of -0.2%, 0.0% and 0.2%. In the Omega framework all the return outcomes below the specified loss threshold level are regarded as a loss and all the return outcomes above the loss threshold are regarded as a gain. Therefore, the loss threshold level chosen refers to investor's preference towards risk: the lower

	Sigma		R_b - VaR				R_b - CFVaR				Semi-stdev.						(I_l)					
			1%		5%		1%		5%		-0.2 %		0.0 %		0.2 %		-0.2 %		0.0 %		0.2 %	
	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank
Panel B: Equity Europe																						
Aktiaeurob	0.012	6	0.031	4	0.022	4	0.048	7	0.022	4	0.009	5	0.009	5	0.009	5	0.396	4	0.502	11	0.558	7
Egarvonkaa	0.014	8	0.030	3	0.021	3	0.039	4	0.021	3	0.008	3	0.008	3	0.008	3	0.382	2	0.483	2	0.559	8
Evliescb	0.009	5	0.022	1	0.016	1	0.035	2	0.016	1	0.006	1	0.006	1	0.006	1	0.355	1	0.493	5	0.586	13
Evlieu50b	0.005	1	0.040	10	0.028	10	0.047	6	0.028	10	0.011	10	0.011	10	0.011	10	0.447	13	0.506	12	0.556	6
Gylleuequb	0.006	2	0.026	2	0.019	2	0.034	1	0.018	2	0.007	2	0.007	2	0.007	2	0.394	3	0.486	4	0.565	10
Mandeugrok	0.017	11	0.041	11	0.029	11	0.059	12	0.030	11	0.012	11	0.012	11	0.012	11	0.419	6	0.498	10	0.561	9
Neurolandk	0.009	4	0.033	6	0.023	6	0.041	5	0.024	6	0.009	6	0.009	6	0.009	6	0.422	7	0.485	3	0.549	3
Neuropak	0.008	3	0.032	5	0.023	5	0.038	3	0.022	5	0.008	4	0.008	4	0.009	4	0.429	10	0.494	7	0.569	11
Opeuosakea	0.015	10	0.045	12	0.032	12	0.058	11	0.031	12	0.012	12	0.012	12	0.012	12	0.434	12	0.496	8	0.545	2
Pohekasvb	0.017	12	0.049	13	0.035	13	0.062	13	0.034	13	0.013	13	0.013	13	0.013	13	0.432	11	0.497	9	0.551	4
Sampoeuosk	0.017	13	0.037	7	0.026	7	0.050	10	0.026	8	0.010	7	0.010	7	0.010	7	0.427	9	0.493	5	0.551	4
Sampoeuvak	0.014	9	0.037	8	0.026	8	0.049	8	0.026	7	0.010	8	0.010	8	0.010	8	0.411	5	0.473	1	0.541	1
Seligeu50a	0.013	7	0.039	9	0.027	9	0.050	9	0.027	9	0.010	9	0.010	9	0.010	9	0.422	7	0.569	13	0.569	11
Panel C: Equity Global																						
Aktiaglobb	0.011	2	0.030	4	0.021	4	0.045	5	0.022	5	0.008	6	0.008	6	0.008	6	0.411	3	0.504	9	0.567	8
Albgloblub	0.011	1	0.029	3	0.021	3	0.036	2	0.021	2	0.008	3	0.008	3	0.008	3	0.413	4	0.502	7	0.569	10
Evliglobab	0.013	7	0.031	6	0.022	6	0.046	7	0.021	4	0.008	7	0.008	7	0.008	7	0.423	7	0.530	10	0.577	11
Fimtekno	0.018	10	0.046	10	0.033	10	0.059	11	0.033	10	0.012	10	0.012	10	0.012	10	0.433	9	0.494	6	0.536	1
Fondita20b	0.015	9	0.039	9	0.028	9	0.055	9	0.029	9	0.011	9	0.011	9	0.011	9	0.434	10	0.493	1	0.549	4
Mandglobak	0.013	8	0.034	8	0.024	8	0.044	4	0.025	8	0.009	8	0.009	8	0.009	8	0.428	8	0.494	4	0.548	3
Mandglotek	0.022	11	0.052	11	0.037	11	0.058	10	0.037	11	0.014	11	0.014	11	0.014	11	0.451	11	0.493	1	0.538	2
Nforestak	0.013	6	0.028	1	0.020	1	0.047	8	0.020	1	0.007	1	0.007	1	0.007	1	0.411	2	0.493	1	0.565	7
Opemetsaa	0.012	4	0.029	2	0.021	2	0.045	6	0.021	3	0.008	2	0.008	2	0.008	2	0.410	1	0.502	7	0.568	9
Opsgloeqa	0.011	3	0.031	5	0.022	5	0.039	3	0.022	6	0.008	5	0.008	5	0.008	5	0.417	6	0.494	4	0.561	5
Selglobala	0.012	5	0.032	7	0.022	7	0.035	1	0.022	7	0.008	4	0.008	4	0.008	4	0.415	5	0.562	11	0.563	6

Appendix 7 Risk proxies and ranking orders: Bond Europe (Panel D), Asset Allocation (Panel E) and Other (Panel F)

This table reports risk proxy values and their corresponding ranking orders for Finnish mutual funds investing in European bonds (Panel D). In addition performance measures and rankings are reported for Finnish Asset Allocation (Panel E) and risk and hedge funds (Panel F). All the risk proxies are estimated from daily returns during observation period of 1999-2003. High risk proxy value yields low ranking, i.e. the riskiest fund gets the last position. Sigma of the Sharpe ratio is estimated from the excess returns distributions. All the other risk proxies are estimated from the gross return distributions. R_b - VaR and R_b - CFVaR are estimated at significance levels of 5% and 1%. The semi-standard deviation is estimated using three different target return levels of -0.2%, 0.0% and 0.2%. In the Reward to semi-variance framework investment risk arises from not achieving the specified target return. The probability weighted losses (I_1) of Omega is calculated at loss thresholds levels of -0.2%, 0.0% and 0.2%. In the Omega framework all the return outcomes below the specified loss threshold level are regarded as a loss and all the return outcomes above the loss threshold are regarded as a gain. Therefore, the loss threshold level chosen refers to investor's preference towards risk: the lower the loss threshold, the less risk averse the investor.

	Sigma		R_b - VaR				R_b - CFVaR				Semi-stdev.						(I_1)					
			1%		5%		1%		5%		-0.2 %		0.0 %		0.2 %		-0.2 %		0.0 %		0.2 %	
	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank
Panel D: Bond Europe																						
Albeubob	0.008	11	0.002	1	0.001	1	0.002	10	0.001	2	0.000	1	0.000	1	0.001	1	0.005	1	0.559	10	0.995	11
Alfeuoblb	0.008	5	0.006	10	0.004	10	0.007	4	0.004	10	0.001	10	0.001	9	0.002	10	0.159	10	0.450	1	0.808	3
Evlieuoblb	0.008	3	0.006	8	0.004	8	0.007	5	0.004	9	0.001	9	0.001	8	0.002	8	0.170	11	0.488	4	0.785	1
Evlieuyhkb	0.008	10	0.002	2	0.002	2	0.003	11	0.002	3	0.000	2	0.001	2	0.001	2	0.026	2	0.530	7	0.982	10
Fimeuro	0.008	8	0.006	9	0.004	9	0.032	1	0.001	1	0.001	8	0.001	10	0.002	7	0.115	3	0.531	8	0.856	9
Hanobliga	0.007	2	0.005	5	0.004	5	0.006	6	0.004	7	0.001	5	0.001	5	0.002	4	0.156	7	0.451	3	0.813	4
Nproeoblk	0.007	1	0.005	6	0.004	6	0.006	8	0.004	5	0.001	3	0.001	3	0.002	6	0.128	4	0.543	9	0.835	8
Pohoblib	0.008	4	0.006	7	0.004	7	0.007	3	0.004	8	0.001	7	0.001	7	0.002	9	0.156	8	0.490	5	0.813	5
Sampooblik	0.008	6	0.005	4	0.004	4	0.007	9	0.004	6	0.001	6	0.001	6	0.002	5	0.140	5	0.450	1	0.824	7
Sampoyoblk	0.008	7	0.005	3	0.004	3	0.006	7	0.004	4	0.001	4	0.001	4	0.002	3	0.144	6	0.493	6	0.820	6
Seleurobla	0.008	9	0.008	11	0.006	11	0.009	2	0.006	11	0.002	11	0.002	11	0.002	11	0.158	9	0.792	11	0.805	2
Panel E: Asset Allocation																						
Abergoptib	0.008	5	0.006	5	0.004	5	0.007	5	0.004	5	0.001	5	0.001	5	0.002	5	0.156	3	0.490	1	0.813	5
Conkorosb	0.014	7	0.022	6	0.016	6	0.032	6	0.016	6	0.006	6	0.006	6	0.006	6	0.361	6	0.478	5	0.600	2
Elvimixb	0.014	3	0.021	3	0.015	3	0.028	3	0.015	3	0.006	3	0.006	3	0.006	3	0.376	4	0.498	6	0.600	3
Gylloptmb	0.015	4	0.031	4	0.022	4	0.040	4	0.022	4	0.008	4	0.008	4	0.008	4	0.405	5	0.482	4	0.557	4
Mandneutrk	0.014	2	0.019	1	0.013	1	0.027	1	0.013	1	0.005	1	0.005	1	0.005	1	0.376	1	0.572	7	0.572	7
Opppirkkaa	0.015	6	0.028	7	0.020	7	0.036	7	0.020	7	0.008	7	0.008	7	0.008	7	0.403	7	0.561	3	0.561	1
Pohforteb	0.014	1	0.002	2	0.001	2	0.003	2	0.000	2	0.000	2	0.000	2	0.001	2	0.005	2	0.593	2	0.974	6
Panel F: Other																						
Confocusb	0.014	4	0.014	5	0.010	5	0.019	5	0.009	5	0.004	5	0.004	5	0.004	5	0.337	2	0.657	3	0.664	3
Gyllmomenb	0.018	3	0.049	3	0.035	3	0.065	4	0.036	3	0.014	3	0.014	3	0.014	3	0.435	2	0.481	2	0.534	2
Mandkontrk	0.018	5	0.048	2	0.034	2	0.069	2	0.034	2	0.013	2	0.013	2	0.013	2	0.432	4	0.482	4	0.537	4
Mandvipuk	0.013	2	0.016	4	0.011	4	0.021	3	0.012	4	0.004	4	0.004	4	0.004	4	0.332	5	0.480	1	0.601	1
Phalanxa	0.024	1	0.031	1	0.022	1	0.034	1	0.021	1	0.008	1	0.008	1	0.008	1	0.434	1	0.534	5	0.587	5